TIME-MANAGEMENT IN EMERGING ADULTHOOD DURING THE TRANSITION TO UNIVERSITY

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Abstract

Attending university for the first time involves a stressful transition for most emerging adults, with a substantial minority of students experiencing serious difficulties and failing to complete their degrees (Wintre & Yaffe, 2000; Wintre & Bowers, 2007). The overarching goal of the present dissertation was to build a theoretical foundation for modelling self-regulation in emerging adulthood during the transition to university, which could be used to inform the design and evaluation of a time-management intervention workshop.

To provide a framework for understanding self-regulation and development during this period, the Regulation Extension to Sameroff's Unified Theory of Development (RESUTD) was proposed. The RESUTD model built on Sameroff's (2010) Unified Theory of Development. Study One used a longitudinal design with a sample of emerging adults transitioning to university to test the proposed RESUTD model. Participant data originated from the Transition to University (T2U) project (Buote et al., 2007; Wintre et al., 2009), a longitudinal, collaborative, multi-site investigation examining undergraduate students' university experiences, with two cohorts of data starting in 2004 and 2005. The final sample that was used for Multi-Level Model (MLM) analyses included data from 1395 participants and 3189 observations across three years. Self-regulation in the academic context was operationalized in the longitudinal study through a questionnaire (Time-Management, for details, see Methods) that gauged various self-initiated behaviours important to time-management at university. External regulation within the academic context was operationalized through a questionnaire (Student Perception of University Support and Structure; for details see Methods) that measured students' perception of the structure and support that their university environment provided for them.

Analyses revealed a significant and notable impact of pre-existing student attributes, including socio-economic status (SES), high school graduating average (HGPA), and gender. Gender was a significant predictor of the intercept of the three outcome measures, such that, female students reported a greater initial level of stress and depressive symptomatology, and lower initial adjustment levels. Both SES and HGPA were also significant predictors of the intercept for student adjustment and emotional

well-being, with higher values on both variables associated with better adjustment and well-being outcomes. Demographic variables differentiated where students started their journey of adjustment in the transition to university (i.e., intercept terms); however, they did not significantly impact the rate of change in adjustment or emotional well-being outcomes (i.e., slope parameters). The analyses also revealed the significant and continuous impact of both internal and external regulatory resources on student adjustment to university and emotional well-being outcomes.

Study Two aimed to develop and evaluate an effective intervention for supporting the improvement of students' self-regulatory skills. A time-management intervention was designed with a focus on teaching students strategies to bolster their internal and external regulatory resources through both enhanced awareness of optimal behaviours, and the use of strategies that can modify the student's environment. In total, 59 students completed the pre-workshop questionnaire and randomly attended the intervention or the control condition workshops. The intervention condition was attended by 34 students, and the control condition, consisting of a facilitated discussion on the challenges of the first year, was attended by 25 students. The students were not aware of the existence of the two separate group conditions that were being offered which formed the basis of randomization. Students completed a second questionnaire at the end of the course, and their final course grade was obtained from their instructor. Being part of the intervention group was predictive of higher grades and accounted for approximately 10% of the variation in the final course grades after controlling for SES and HGPA. Compared to the control group, academic adjustment scores of the students in the intervention group increased after the workshop with a large effect size; and the perceived stress scores of the students in the intervention group had decreased, with a medium effect size. Furthermore, these changes were related to the increase in time-management skills and students' reported knowledge in the domains targeted by the intervention. Implications for future research and the application of the findings to intervention efforts are discussed.

Acknowledgements

The road to finishing this thesis has been a long one, so long that many had good reason to doubt if it will ever be done! Thanks to the support of countless individuals, here we are at the end of the road with a completed dissertation that one could be proud of. First and foremost, I want to thank my supervisor, Dr. Maxine Wintre, for her guidance, support, patience, encouragement, and unbelievable turnaround time! I would also like to express my gratitude to my committee members, Dr. Cribbie and Dr. Pepler, whose feedback greatly shaped and improved the thesis. Dr. Cribbie, your longitudinal methods course allowed me to do the awesome longitudinal analyses for Study One, and Dr. Pepler, taking your program evaluation course inspired me to design and evaluate the intervention in Study Two. Thank you to the entire Wintre Lab for their enduring support, encouragement, and the helpful mock defense. I am grateful to Dr. Desrocher for her heartful support of clinical students during the challenging residency application process that often accompanies much of the dissertation work.

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Introduction: Time-management in Emerging Adulthood During the Transition to University

In Plato's *Protagoras* (ca. 380 BC), Socrates asks a fundamental question that we still face to this day: how is it possible that we lack command over ourselves? (Plato, 1986) We may have all faced this question at some point, after having tried and failed at keeping a diet, broken a New Year's resolution, or acted against our own prior decisions and commitments. This frailty often leads to the experience of *akrasia*, that is, the state of acting against one's better judgement. The question of *akrasia* continues to be investigated in contemporary psychology under various conceptual frameworks, such as delay of gratification, time-management, self-control and other constructs that can be encompassed in the concept of self-regulation (Myrseth & Fishbach, 2009).

In the context of the transition to university, a number of researchers have looked at students' ability to self-regulate, or "time-manage," given their busy schedules that combine academic, social and personal activities (for a review see: Claessens, Eerde, Rutte, & Roe, 2007). In these studies, time-management was operationalized in terms of "behaviours that aim at achieving effective use of time while performing certain goal-directed activities" (Claessens et al., 2007). For example, Lahmers and Zulauf (2000) studied the relationship between time spent studying, the amount of time spent in class, and time-management ability in relation to grade point average (GPA). They found that although time spent studying was positively related to GPA, the association of time-management ability with GPA was of a higher magnitude, suggesting that time-management abilities are important with regard to students' academic achievement.

Given the importance of time-management skills to student success, the Vice Dean of Teaching in the Faculty of Health at York University invited a proposal for a time-management intervention for students in their first year of study. We designed an intervention that was informed by Sameroff's regulatory model (Sameroff, 2010), which we developed further to apply to emerging adults transitioning to university. In the first chapter of the present thesis, Sameroff's Unified Theory of Development is examined with a focus on its regulatory component and application to university students. An extension to Sameroff's regulatory model is proposed (Regulation Extension to Sameroff's Unified Theory of Development: RESUTD) and tested using data from a longitudinal study of students attending six Canadian universities. In the second chapter of this thesis, insights drawn from testing the proposed theoretical framework are used to evaluate the time-management intervention designed for York University and the ensuing data that were collected. The intervention was carried out during the winter semester of 2017 with both baseline and post-intervention data collection.

Emerging Adulthood and the Transition to University

Attending university for the first time involves a stressful transition for most youth, with a substantial minority of students experiencing serious difficulties and failing to complete their degrees (Pantages & Creedon, 1978; Wintre & Yaffe, 2000; Wintre & Bowers, 2007). Furthermore, for most students, this transition to a higher level of education occurs within the transition to adulthood. Emerging adulthood (Arnett, 2000; 2006) is the period of development between adolescence and adulthood (ages 18 to 29 approximately) for young people living in industrialized countries (Arnett, 2012). Arnett (2012) notes that there is no definite age when emerging adulthood ends and young adulthood begins. Indeed, for some young people, emerging adulthood may end by the mid-twenties (Arnett, 2000). However, in the United States, Canada, and some Westernized countries such as Australia and Japan, demographic trends in marriage and parenthood indicate that the median age of these life events is closer to 30 years, suggesting that the age range of 18 to 29 is fitting as a rough age range for the period of emerging adulthood. Thus, in the present study, we sampled 18 to 29-year-old students, which best fits Canadian demographic trends.

As a developmental stage, emerging adulthood is characterized by identity explorations in the areas of work and education, relationships, morals, and values. According to Arnett (2012), the primary feature that distinguishes emerging adulthood from young adulthood is a developmental concept referred to as role immersion. While extending their formal education, many emerging adults take on jobs that will not lead to a long-term career but serve to provide financial support to subsidize their education, leisure activities, world travels, or provide early experience in a particular field of work (Arnett, 2006; 2012).

The emerging adults' exploration of pathways and variability in pursuits are also seen within educational contexts. For example, emerging adults may begin a post-secondary education program at one institution and decide to transfer schools to pursue a different program (Wintre & Morgan, 2009). Research on emerging adulthood underscores both the transient quality of emerging adults' lives and the heterogeneity in the demographics of this stage of life (Arnett, 2000; 2006). Arnett (2006) describes emerging adulthood as characterized by instability due to emerging adults' explorations of different possibilities in their education, romantic relationships, living arrangements, work, and sense of self. Schulenberg and Zarrett (2006) describe the distinctive features in the transition to adulthood as including extensive changes in personal and social roles, "heterogeneity in life paths, and decreased institutional structure coupled with increased agency" (p. 140).

According to Arnett (2007), during this developmental period, most emerging adults leave their parents' house and are less exposed to parental influence. Those who stay home tend to be more autonomous than during adolescence. Emerging adults tend to spend more time alone than any age group except the elderly. Overall, there is a marked reduction in the structure provided by the emerging adults' external environments: "Emerging adulthood is a self-focused age when social control is at an ebb, and people have the greatest freedom to focus on their self-development" (Arnett, 2007, p.213). The diminution of the external structure is paralleled in the emerging adults' academic environment where:

> "…the amount of time spent receiving direct instruction is relatively small, compared to secondary school. More learning is done through assigned work that the students do on their own. Instructors are less likely to monitor whether or not the students come to class. Thus, schooling in emerging adulthood requires greater capacities for self-regulation in order to succeed." (Arnett, 2007, p.223)

With this increased independence from parents, emerging adults are afforded opportunities to explore multiple life directions in the fields of love, work, and world beliefs (Arnett, 2000). However, most emerging adults remain only semi-autonomous, continuing to rely on parents and institutions (e.g., university, military) to scaffold, by providing support, structure and resources, for their prolonged entry into adulthood (Arnett, 2006; 2012).

Taking into account the importance of regulatory processes, Sameroff identifies a regulation model as a key component of understanding human development in his Unified Theory of Development (Sameroff, 2010). Over the next chapters, we will extend Sameroff's seminal theoretical framework, and use it empirically to investigate data from a three-year longitudinal study of students from six Canadian universities. Subsequently, the implications of an extension of Sameroff's model will be explored specifically in terms of developing intervention strategies for emerging adults during their transition to university.

Theoretical Framework: Sameroff's Unified Theory of Development

The bases of Sameroff's model of the contextual process can be traced to Bronfenbrenner's (1977) model of social ecology, which described the influence of a variety of social settings and institutions on the individual. Sameroff (2010) posits four interacting processes that are essential for understanding human growth. These processes include *personal change*, *context*, *representation* and *regulation*. The personal change process accounts for the increasing complexity of the individual moving from the sensorimotor functioning of infancy to the intricate levels of cognition in adulthood. The contextual process describes the expanding social world in which the individual is immersed and undergoes experiences that can both hinder or augment development (see Figure 1). The representational process accounts for cognitive structures that encode experience at abstract levels, such as language and other symbolic information. Last, and most relevant to the current research endeavour, is the regulation process. Human regulation expands from basic biological regulation such as body temperature and hunger to higher order behaviours such as the regulation of attention, complex behaviour, and social interactions (Sameroff, 2010).

Although regulatory processes are present throughout the biological and psychological spheres in Sameroff's unified model, only the latter is pertinent to the current examination of self-regulation (in relation to the transition to university) as it can inform intervention design. Figure 2 displays the regulation process labelled by Sameroff as the ice-cream-cone-in-a-can model of development (Sameroff & Fiese, 2000). The cone shape of Sameroff's regulation model denotes two important concepts: the importance of other-regulation and the expanding role of self-regulation (Sameroff, 2010). Children self-regulate in a social surround that is actively engaged in other-regulation. This balance between other-regulation and self-regulation shifts as children are able to take more responsibility for their own well-being (Sameroff, 2010). The arrows represent the transactional interplay between the two, as for example the increases in social responsibility are paced to the successful acquiring of previous self-regulatory skills (Rogoff, 2003). Sameroff's regulation model provides a potent framework that takes into account developmental and transactional perspectives on regulation that are integrated into the broader unified theory.

Figure 3 depicts the integration of three of these models across the lifespan while leaving out the growth in abstract representation processes. General growth and expansion in the regulatory process, which encompasses the personal and biological spheres, is evident across time. This expansion, however, is not linear and is characterized by periods of relative stagnation or precipitous change. Sameroff borrows this concept from evolutionary theorists Gould and Eldredge (1977), who labelled these periods of rapid change as *punctuated equilibrium* when large changes in the environment or the person push development towards new states of equilibrium. Transition to university within the context of emerging adulthood is posited to be one such case of punctuated equilibrium when the individual needs to adapt to demanding internal and external changes.

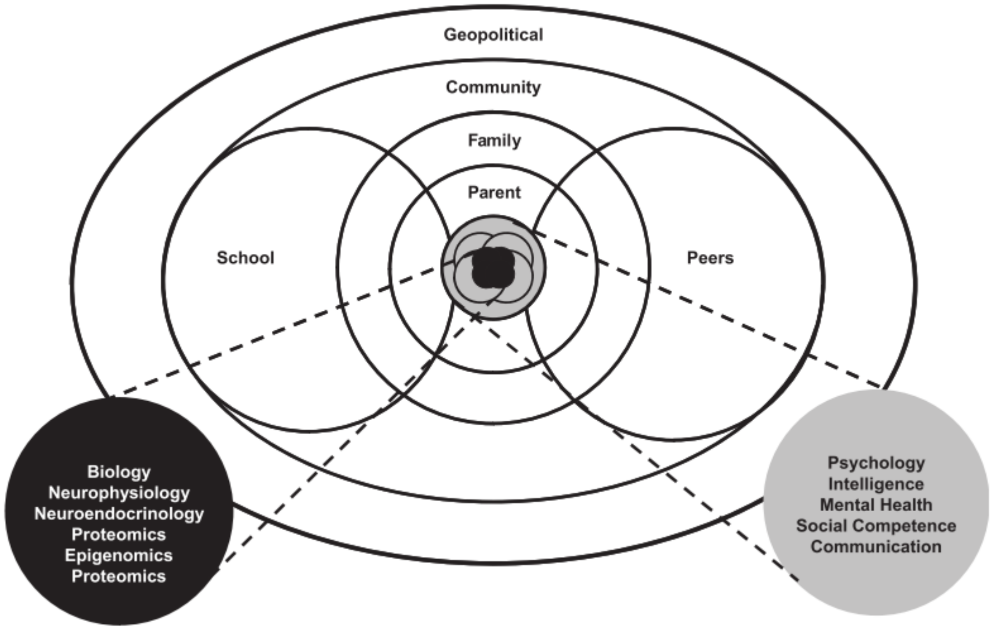

Figure 1
Biopsychosocial ecological system (Sameroff, 2010).

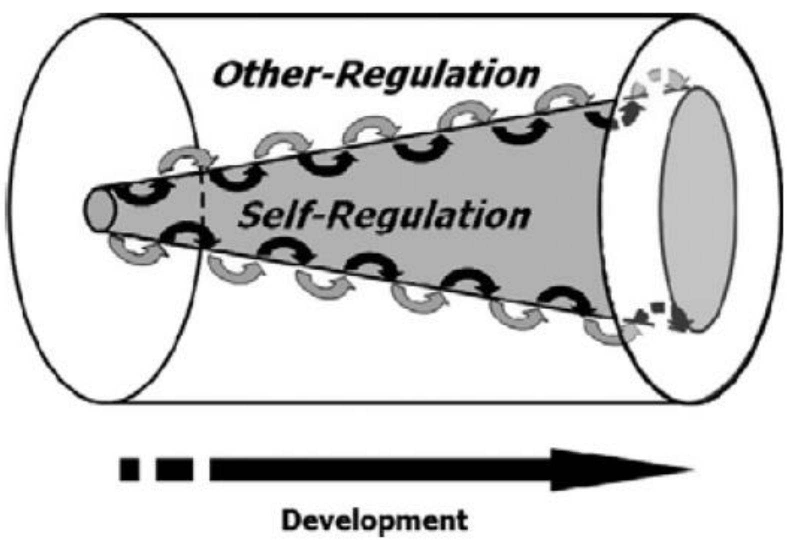

Figure 2
Sameroff's ice-cream-cone-in-a-can model of self-regulation and other-regulation (Sameroff, 2010).

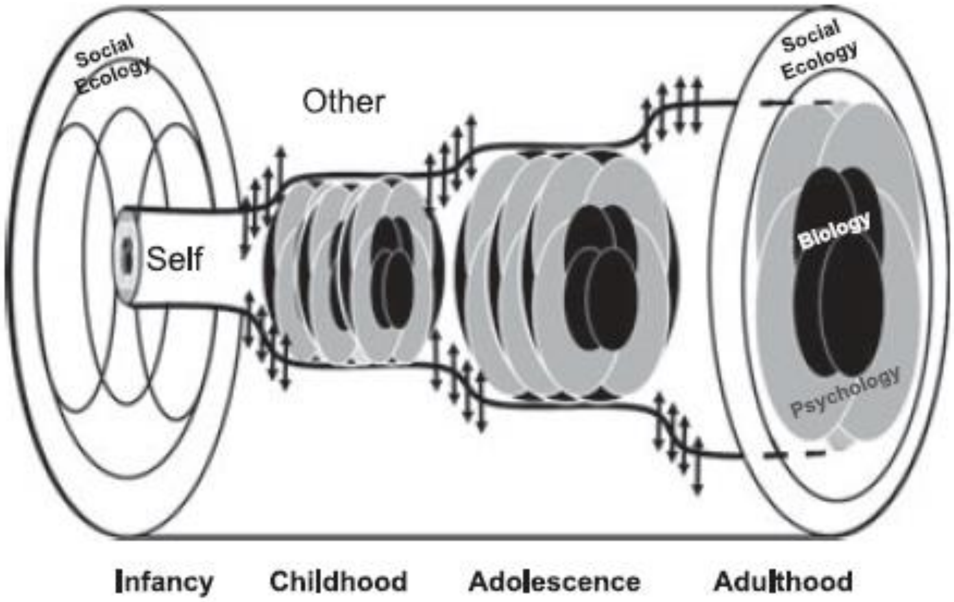

Figure 3
Sameroff's unified theory of development including the personal change, context and regulation models (Sameroff, 2010).

Regulation Extension to Sameroff's Unified Theory of Development

The proposed Regulation Extension to Sameroff's Unified Theory of Development (RESUTD) introduces three new concepts (external-regulation, behavioural space, and entropy) to Sameroff's seminal work. Sameroff (2010) emphasized the importance of other-regulation in his regulation model. Self-regulation happens within a context, a social surround that is actively engaged in "other"-regulation, as Sameroff (2010) argued:

> "It is parents who keep children warm, feed them, and cuddle them when they cry; peers who provide children with knowledge about the range and limits of their social behaviour and teachers who socialize children into group behaviour as well as regulate cognition into socially constructed domains of knowledge." (pg. 15)

Parents can directly modify the environment to circumscribe the possible range of behaviours available to the child (e.g., put the cookie jar out of reach; lock the liquor cabinet).

They also scaffold regulatory behaviours not fully mastered by the child by facilitating parts of the task while letting the child carry out the rest. Teachers can make the discrepancy between the child's current performance and the desired behaviour more salient by providing relevant and timely feedback. These influences are often transactional in nature and manifold, going beyond the parent-child transactions to include the relations between the family, cultural, economic and political situations (Sameroff, 2010).

As the range of other-regulators can comprise more than just people (e.g., appliances), we propose the term *external-regulation* to replace *other-regulation* to better reflect this concept and its corollaries with regard to the use of environmental tools for the regulation of behaviour. To illustrate this point, consider the many tools humans use today to help regulate their behaviours: from a biological level (e.g., heart pace-maker, glucose meter), to personal behavioural regulation (e.g., alarm clocks, calendar reminders), to a social level (e.g., traffic signals). An interesting example of such a tool is the *Freedom* computer software, which can block a person's Internet access for a duration chosen by the person to avoid distractions (Stutzman, n.d.). This example is particularly interesting as it shows how individuals actively use tools to externally regulate when the same behaviour could potentially be achieved through internal resources.

There are many other examples of individuals using external-regulation instead of relying on internal resources. For example, in a study involving undergraduate students at the start of a course, they were given a choice between having three different deadlines for their papers over the duration of the semester or have all three papers due at the end of the course. Even though there were no gains for handing the papers in early, and penalties for late work, students overwhelmingly chose to have the deadlines spread across the course, to help them improve their time management (Ariely & Wertenbroch, 2002).

Although in Sameroff's regulation model, the balance between self and other regulation shifts through development resulting in reduced external-regulation, this does not imply that self-regulation is superior to external-regulation. Even though an individual might have the *capacity* to self-regulate a particular behaviour, rather than rely on external-regulation, the choice between the two depends on the situation, particularly given a large body of research that shows self-regulation draws on a limited resource (Muraven & Baumeister, 2000). Various studies have shown that when a situation demands two consecutive acts of self-regulation, such as inhibiting an impulse or resisting temptation, performance on the second act is frequently impaired. The impairment is found even if different behaviours needing self-regulation are involved, such as resisting temptation and overwriting well-learned impulses in response to certain stimuli (Muraven & Baumeister, 2000). These research findings suggest that occasionally it is more optimal to rely on external-regulatory aids, than to overwork internal resources to regulate behaviour towards a goal.

A closer examination of Sameroff's (2010) regulation model (Figure 2) reveals that the total quantity of behaviour being regulated is always constant, divided between self-regulation and external regulation. To apply this model to situations where the regulatory demand on the individual varies, we propose an addition to the model where the total quantity of behaviour that is required to be regulated to fulfill a goal is circumscribed and labelled *behavioural space* (Figure 4). This concept, behavioural space, allows the illustration of the relative change in behavioural demands specific to certain tasks and between situations. To demonstrate this idea, the general increase in academic demand is delineated in the model by an increase in behavioural space from Grade 3 to Grade 5 (see Figure 4). This increase in behavioural space implies that there are more behaviours that need to be regulated, either internally or externally, for the goal (i.e., academic advancement to the next level) to be achieved. In Figure 4, aside from the increase in behavioural space, there is a decrease in the portion of behavioural space regulated externally and a corresponding increase in the portion that is self-regulated.

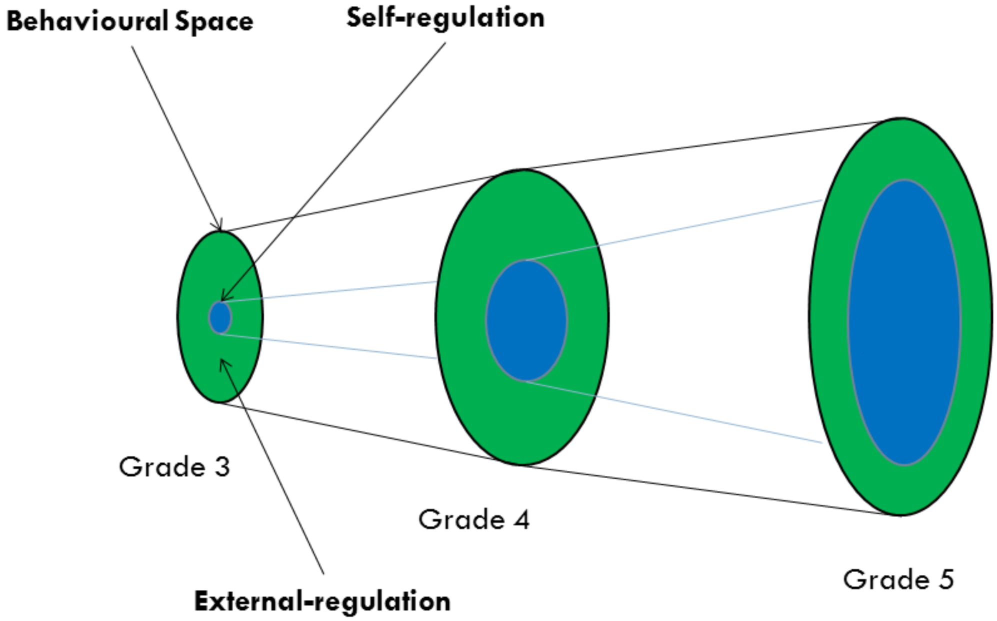

Figure 4
Regulation model showing increase in behavioural space and a shift towards self-regulation across academic development (Chavoshi, 2019).

The increase in behavioural space denoting greater complexity of tasks requiring regulation across development, as proposed by Sameroff's (2010) unified theory, is analogous to Vygotsky's (1978) zone of proximal development (Sameroff, 2010). In this expansion, behaviour that previously required external regulation is learned to be self-regulated by the person, and the difference between the two states would constitute the proximal zone of development: regulatory behaviour that the child is eventually capable of learning and internalizing but at first needs to be externally regulated. For healthy development, this reduction in external regulation should be developmentally appropriate; that is, it should not be more than the zone of proximal development, yet not too stringent as to hinder the development of self-regulatory abilities (Silk, Morris, Kanaya & Steinberg, 2003).

What happens when external regulation is removed beyond what is developmentally appropriate, or the individual does not have the self-regulatory skills to manage a particular demand, i.e., when behaviour is *not* regulated? For example, consider the case of a neglected child where there is a large absence of external regulation, or the case of an individual who does not have sufficient internal resources due to fatigue, or because of the influence of drugs to self-regulate. In both of these cases, there are failures of regulation; however, they cannot be illustrated in Sameroff's regulation model (Figure 2). We propose the addition of a concept depicted in Figure 5 as "entropy" which illustrates the failure or lack of regulated behaviour (either internally or externally) in relation to the behavioural demands of a particular activity or goal. In Figure 5, entropy can be seen in the portion of the total behavioural space (i.e., the net amount of regulated behaviour required to meet a certain goal), that is not covered either by self-regulation or external regulation. Entropy is a term borrowed from the natural sciences which is defined as the level of disorder present in a system.

In the case of emerging adults transitioning to university, we hypothesize that the implications of entropy within their academic behavioural space will manifest in lower grades, indicating that students are not able to sufficiently regulate their behaviour to meet the post-secondary academic demands. Furthermore, we posit that such presence of entropy will lead to more than a failure to achieve satisfactory grades, but may also involve emotional sequelae such as heightened anxiety and lower mood due to feelings of being overwhelmed.

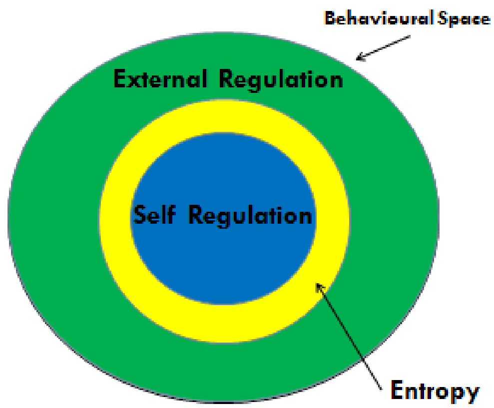

Figure 5
A slice of the regulation model depicting entropy, self and external regulation bounded by the behavioural space (Chavoshi, 2019).

Self-Regulation and the Transition to University in Emerging Adulthood

The Regulation Extension to Sameroff's Unified Theory of Development (RESUTD) introduces the concepts of external regulation, behavioural space, and entropy to Sameroff's (2010) regulation model. We next examine the proposed RESUTD model in the context of emerging adulthood and the transition to university. During the developmental period of emerging adulthood, there is increasing financial and social independence from parents that afford emerging adults opportunities to explore multiple life directions in the fields of love, work, and world beliefs (Arnett, 2000). Although emerging adults develop greater independence, most remain only semi-autonomous, continuing to rely on parents and institutions (e.g., university, military) to scaffold their prolonged entry into adulthood (Arnett, 2006; 2012).

From an academic perspective, the reduction in external-regulation, coupled with increased demands in university, may result in substantial entropy, as evidenced by the high attrition rates during the first year of post-secondary studies (Finnie & Qiu, 2009). In Figure 6 we illustrate the development of academic demands as the adolescent develops into emerging adulthood and starts attending a post-secondary institution. In the figure, we show that even with the expansion of the emerging adults' self-regulatory capacity over time (the blue shaded region), there is still a gap left by the expansion of the behavioural space (total academic demands placed on the individual) and the reduction in the amount that was formerly externally regulated (i.e., structure and support provided in high school vs the more laissez-faire supervision provided in university).

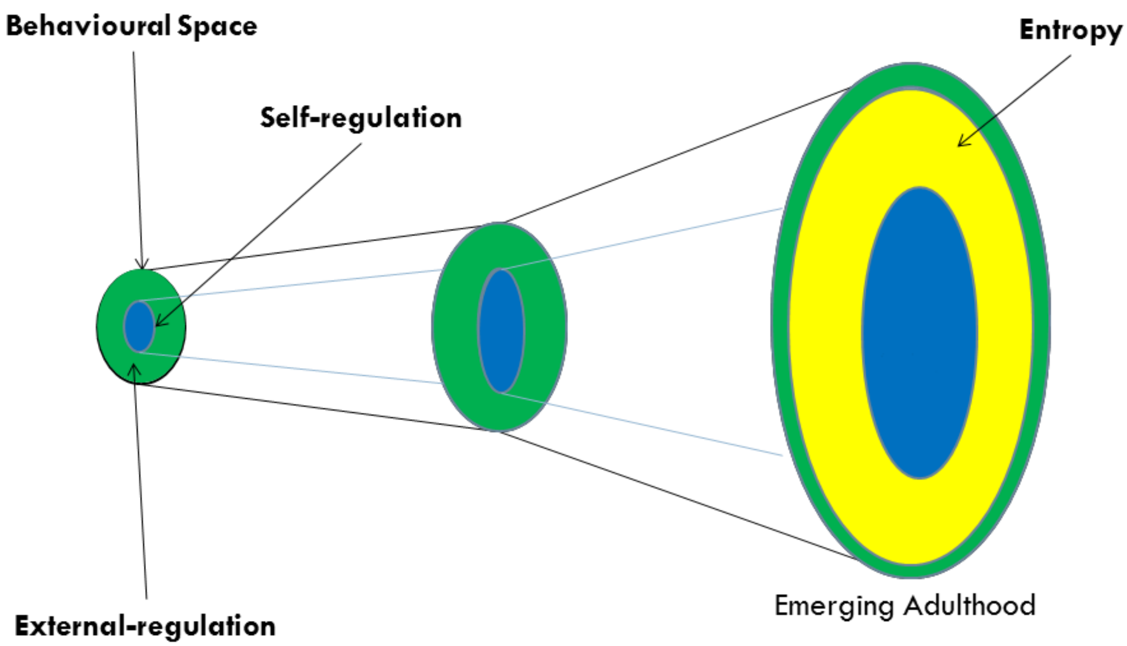

Figure 6
Increase in behavioural demand coupled with a reduction in external regulation evident in emerging adulthood results in signification regulatory entropy during transition to university (Chavoshi, 2019).

Study One: Longitudinal Empirical Examination of Regulation Extension to Sameroff's Unified Theory of Development Model During the Transition to University

Sameroff (2010) suggested a continuous developmental increase in self-regulation, paralleled by a continuous decrease in social or external regulation from infancy to adulthood. The importance of self-regulation skills predicting children's early school success has been studied widely, and poor self-regulation has been linked to high rates of expulsion (Morrison, Ponitz, & McClelland, 2010). In line with Sameroff's regulatory framework, research has shown that successful self-regulation depends on environmental influences and interactions with others, as well as child factors and predispositions (Morrison et al., 2010). Although the importance of self-regulatory skills (i.e., time-management) during the university transition has been examined by a number of researchers, the development of self-regulation, and the influence of support and structure from the institution scaffolding this development has not been previously longitudinally examined (Claessens et al., 2007).

The objective of this first study was to test the RESUTD model (see Figure 6) with a sample of emerging adults transitioning to university. The study capitalized on a longitudinal study of emerging adults transitioning to university to examine the transaction of self and external regulation and their impacts on a number of outcome measures including adjustment to university and psychological well-being. First, we hypothesized that students who enter university with greater self-regulatory skills are less affected by the reduction in external-regulation and experience less behavioural entropy during their transition to university (Figure 7a). Second, those who have not developed adequate self-regulatory skills will still transition successfully if they receive adequate environmental support and structure (i.e., external-regulation, see Figure 7b). Third, the students who have not developed adequate self-regulatory skills during their first year, if provided with adequate external-regulation, will go on to develop better self-regulatory skills that will be evidenced in the following years. Finally, students who do not have adequate self-regulatory skills during the first year and who do not receive adequate external-regulation experience entropy which will manifest in academic and psychological difficulties (Figure 7c).

Self-regulation in the academic context was operationalized in the longitudinal study through a questionnaire (Time-Management, for details, see Methods) that gauged various self-initiated behaviours (e.g., studying in a distraction-free environment, keeping up with course work, attending lectures and tutorials) important to time-management at university. The Time-Management questionnaire has been previously used in research examining student transition from high school to university (Wintre et al., 2011). External regulation within the academic context was operationalized through a questionnaire (Student Perception of University Support and Structure; SPUSS; Wintre, Gates, Pancer, Pratt, Polivy, Birnie-Lefcovitch, & Adams, 2009) that measured students' perception of the structure and support that their university environment provided for them.

We conceptualized the effects of entropy in a number of ways. First, students who report high levels of adjustment to university are meeting the regulatory demands put on them by their university education (i.e., the behavioural space) successfully through a combination of both internal and external regulation. Therefore, a high level of adjustment would be an indication that the behavioural space does not contain significant entropy (e.g., Figure 7a). To measure adjustment to university, we utilized the Student Adaptation to College Questionnaire (SACQ; Baker & Siryk,1989) that is based on a multifaceted view of student adjustment including such domains as academic adjustment, social adjustment, personal-emotional adjustment, and institutional commitment. The multifaceted approach utilized by the SACQ has been advocated by many researchers (Spady, 1971; Terenzini & Pascarella, 1977; Tinto, 1996; Wintre & Bowers, 2007).

Second, a significant presence of entropy may lead to students feeling overwhelmed, inadequate, and defeated due to the inability to meet the demands of their post-secondary education successfully. As such, they may experience more frequent difficulties with mood and anxiety. Research has shown that the majority of university students experience high levels of stress (Cottom, Dollar, & de Jonge, 2002; Dixon & Kurpius, 2008). For example, during the transition to university individuals are confronted with new demands that may exceed their existing coping abilities (Dyson & Renk, 2006). Together, these findings indicate that stress is a prominent risk in the adjustment of emerging adults during their transition to university, therefore, it was included as the outcome measures of interest. The experience of stress was operationalized in this longitudinal study through a questionnaire (Perceived Stress Scale; Cohen, 1986) that assessed students' perceptions of stress.

Finally, symptoms of depression were also included as a relevant outcome of difficulties in adjusting to university. Research has shown that elevated personal and academic stress in college and university students predicts depressive symptomatology (Dyson & Renk, 2006; Murphy & Archer, 1996). This is particularly relevant since epidemiological findings indicate that many mental health problems first develop in emerging adulthood (Kessler et al., 2007). For example, 25% of emerging adults experience a depressive episode by age 24 and depression is the most common disorder experienced by emerging adults (Grant & Potenza, 2010; Kessler et al., 2005; Mackenzie et al., 2011; Schulenberg & Zarrett, 2006).

Gender and socioeconomic status have been previously shown to be associated with adjustment and mental health outcomes during the transition to university and were therefore also included in the analyses (Astin 1993; Enochs & Roland, 2006; Wintre & Yaffe, 2000). Participant data for Study One originates from the Transition to University (T2U) project (Buote et al., 2007; Wintre et al., 2009; Wintre et al., 2011; Busseri et al., 2011). The T2U project was a longitudinal, collaborative, multi-site investigation examining undergraduate students' university experiences. Incoming students were randomly selected from among those entering their first year of university directly from a Canadian high school. Two cohorts of students participated, spanning four years of undergraduate education. The first cohort was contacted, prior to the beginning of the first year in university, in the summer of 2004; and the second cohort was contacted in the summer of 2005. For the present study, we will be using data from both cohorts that were collected during their first three years at university.

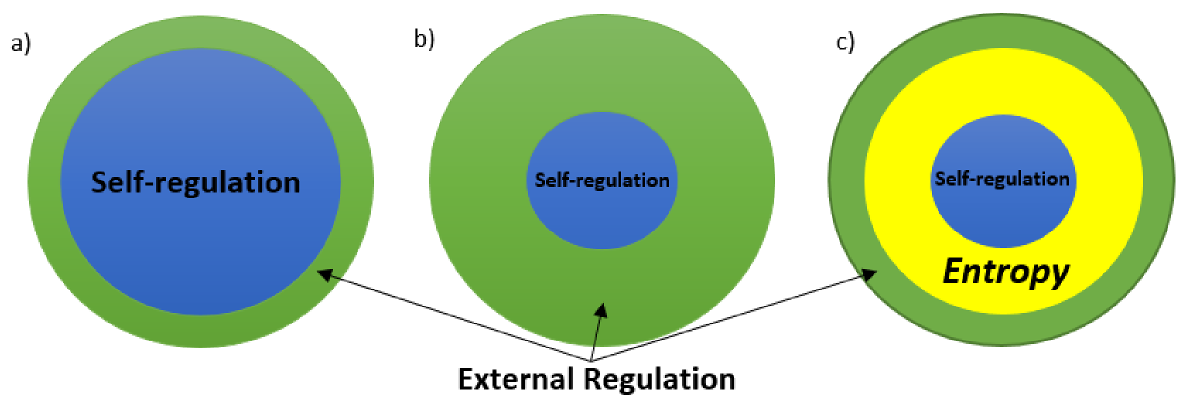

Figure 7
Different combinations of external and self-regulation that allow a student to meet their academic demands (a & b), and the presence of entropy (c) when there is a deficit in either and/or external regulation (Chavoshi, 2019).

Research Questions and Hypotheses

The analyses were designed to address the following research questions and their corresponding hypotheses, rooted in the theoretical framework presented earlier (see Figure 7):

1. How do demographic measures and high school GPA (HGPA) predict the trajectories of students' adjustment to university and emotional well-being over time?
    a. It is hypothesized that both the intercept and slope of the trajectory of adjustment scores (SACQ) will be impacted by demographic measures, including SES and HGPA, such that students with higher perceived SES and higher HGPA will have higher starting adjustment scores that increase to a greater degree over time. Gender is not hypothesized to be a significant contributor to the statistical model in predicting SACQ.
    b. It is hypothesized that both the intercept and slope of the trajectory of stress and depression scores will be impacted by demographic measures, including SES and HGPA and gender, such that students with higher perceived SES and higher HGPA will have lower starting stress and depression scores that either decline or increase to a lesser degree over time. Gender is hypothesized to impact the intercept of depression and stress trajectories; such that female students report a greater initial level of stress and depressive symptomatology.
2. How do the time-varying predictors of Time-management (TM) and Student Perception of University Support and Structure (SPUSS) impact the trajectories of students' adjustment to university and emotional well-being over time?
    a. In addition to the effect of demographic measures, it is hypothesized that adjustment scores will be uniquely predicted by both TM and SPUSS scores, such

that higher scores on these process measures (variables that are part of, and may change, during the transition process) will result in a higher score on adjustment scores. Similarly, it is hypothesized that the outcome variables of stress and depression will be uniquely predicted by both TM and SPUSS scores, such that higher scores on the process measures will result in lower scores on stress and depression outcomes.

   b. We hypothesized that the effect of self-regulatory skills and external-regulation combine to moderate adjustment and emotional well-being outcomes, such that students who enter university with greater self-regulatory skills would be less affected by the reduction in external-regulation (Figure 7a). Similarly, students with underdeveloped self-regulatory skills will transition successfully if they receive adequate environmental support and structure (see Figure 7b). Finally, students who do not have adequate self-regulatory skills during the first year and who also do not receive adequate external-regulation will experience entropy.

3. Exploratory analyses will be conducted to examine the trajectories of TM and SPUSS given available data used in the T2U study. How do demographic measures and high school GPA, and the transactions between TM and SPUSS, explain their respective trajectories over time?

   a. We hypothesized that students would develop their self-regulatory skills over time given external scaffolding in the form of support and structure from the university. As such, TM scores are expected to be associated with SPUSS.

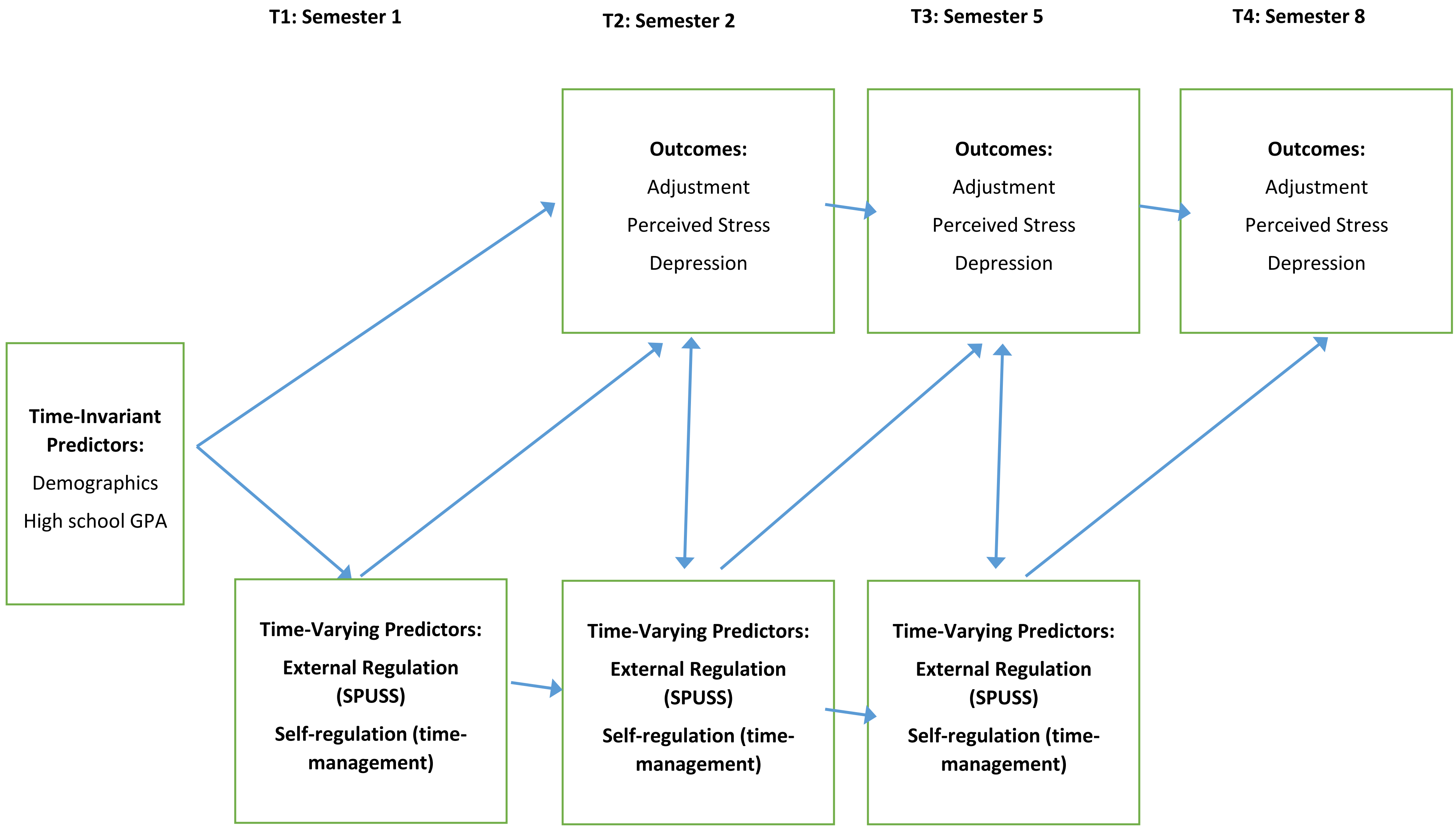

Figure 8
The design of the Multi-Level Model analysing the impact of Time-Invariant, and Time Varying Predictors on the Outcome measures of Student Adjustment, Anxiety and Depression.

Study One: Method

Participants and Procedures

The data used for this study come from the Transition to University (T2U) project, which was a multi-site, multi-investigator research effort developed to explore the experiences of Canadian undergraduates. Participants were incoming students, directly from high school, at six sites: Guelph University, Memorial University of Newfoundland, Mississauga Campus of the University of Toronto, St. George Campus of the University of Toronto, Wilfrid Laurier University, and York University. The number of students invited to participate from each cohort and campus is presented in Table 1. Inclusion criteria included graduation from a Canadian high school and first time attending a post-secondary institution.

During August 2004 and 2005, prior to entering university, two cohorts of first-year students were sent, via mail, a participant package. This package included an introductory letter, a cover sheet for identifying and contact information, the 12-page questionnaire and a postage paid return envelope. The introductory letter explained the purpose of the Transition to University (T2U) study and students were requested, if interested, to complete the consent form and survey package. Responses were accepted from students until midway through the first week of classes (i.e., the first week of September). During the students' first year, questionnaires were sent out in November and March, and for the following three subsequent years, questionnaires were only sent out in March. The March data collection date was chosen to coincide with the end of the semester and capture the experiences of the students during each academic year.

After the initial questionnaire in August, all subsequent surveys were completed through the internet. The universities offered different incentives to their students to complete the survey, including one mark towards the participants' introductory psychology course (restricted to sites where the study investigators were able to offer this incentive), a cash payment of $10.00, or a chance to win one of five $500.00 cash prizes.

Description of University Sites. The reason the Transition to University study recruited participants from six different Canadian universities was to investigate different university and city environments. York University and the University of Toronto (St. George campus) are large, ethnically diverse schools, with over 50,000 students, where a majority of the student body commutes from their parents' homes. Both campuses are located within a large metropolitan city with a population of over two million. The University of Guelph and Wilfred Laurier University are medium-sized universities (i.e., over 10,000 students) located in cities with populations over one hundred thousand. The Mississauga campus of the University of Toronto is ethnically diverse and urban, but with a smaller student body (i.e., less than 10,000 students) when compared to the St. George campus. Finally, Memorial University of the province of Newfoundland and Labrador is smaller, residential, and more homogeneous in terms of its student body. Memorial's student population totals approximately 15,000.

Table 1
Students Contacted for Participation in Longitudinal T2U Study

	Males 2004 Cohort	**Females 2004 Cohort**	**Males 2005 Cohort**	**Females 2005 Cohort**
Guelph*	900	600	1200	600
Memorial	739	568	755	600
UTM	900	600	751	600
UTG	900	600	1200	600
WLU	900	559	1084	600
York	900	600	1200	600

Notes: 4 of the Guelph student addresses were for students living outside Canada, and were not sent. One was returned by the post office. A total of 8807 students were contacted in the 2004 sample. In the 2005 sample, 6 letters from UT (3 males, 3 females), 4 from WLU (all males) were returned by the post office. A total of 9780 students were contacted.

2004 and 2005 Cohort Data Collection Procedures. During November participants who had responded to the August mailed data collection request were emailed regarding the November survey. The e-mail letter contained a link to the web-based survey and gave them the option of requesting a paper copy of the survey. There was a reminder notice sent a week later and then again in December. Participants who continued were contacted again in March for the spring data collection with two reminders sent over April. During their second year, continuing participants were contacted the beginning of March, with reminder emails sent over the next two weeks. During their third year of studies, participants were initially contacted again in March. Introductory letters were sent to all students who had not withdrawn from our research, and who were still in university to invite them to complete the online survey. Reminder emails were sent at the end of March with a second and final reminder sent in the first week of April. The response rate for both cohorts is presented in Table 2

Table 2
Completed Responses by the 2004 Cohort Across the Participating Universities.

	Summer pre 1st Year	**Fall 1st Year**	**Spring 1st Year**	**Spring 2nd Year**	**Spring 3rd Year**
Guelph	552	393	320	204	181
MUN	542	283	244	154	120
UTM	333	213	168	96	75
UTG	404	259	197	132	106
WLU	557	363	289	164	135
York	498	328	236	129	110
Total	**2887**	**1839**	**1454**	**879**	**727**

Measures

Demographic variables. Demographic information was collected in August 2004 and 2005 respectively for each cohort. Variables included participant's age, gender, family composition, parents' income, parents' educational attainment, immigrant/generational status, parental work status, high school grade point average, and intended major. (Other demographic data collected but not used in the current study, are described in Appendix B)

The Center for Epidemiological Study of Depression Scale (CES-D; Radloff, 1977). This 20-item scale assesses the prevalence of depressive symptoms. Respondents are asked to indicate how often they experienced various symptoms in the last week on a four-point scale ranging from 0 (rare) to 3 (most of the time). An example of a statement is, “I was bothered by things that usually don't bother me.” The reliability of the scale in the present sample, measured by Cronbach’s alpha (α), ranged from .90 to .92 across the three data collection periods.

Students’ Perception of University Support and Structure (SPUSS; Wintre, Gates, Pancer, Pratt, Polivy, Birnie-Lefcovitch, & Adams, 2009). This 21-item questionnaire measures the students’ perceptions of university support and its bureaucratic structure. An example of a support item is “If a student needed help for an emotional problem, it would be easy to find a service on campus to help them”, whereas an example of a structure item is “Professors in classes make it clear what students are expected to do in order to get a good grade on assignments, papers and tests”. Items were rated on a 9-point rating scale ranging from -4 (very strongly disagree) to +4 (very strongly agree). Higher scores on the scale indicated a better perception of university support and structure. The reliability of the scale in the present sample ranged from $\alpha = .87$ to .89 across the three data collection periods.

Perceived Stress Scale (PSS; Cohen, 1986) This scale assesses respondents’ perceptions of stress during the past month using 14 items (e.g., “How often have you felt you were effectively coping with important changes that were occurring in your life?”). Respondents indicated how often they had experienced each item on a five-point scale ranging from 0 (never) to 4 (very often). Higher scores reflect greater perceived stress. The reliability of the scale in the present sample ranged from α = .84 to .90 across the three data collection periods.

Student Adaptation to College Questionnaire (SACQ; Baker & Siryk, 1989). The SACQ is a 67-item questionnaire that measures college or university adjustment. It has four subscales of adjustment, including a 24-item Academic Adjustment subscale, measuring self-perceptions of coping with the academic demands of the university (e.g., “I am enjoying my academic work at university.”); a 20-item Social Adjustment subscale that measures interpersonal adaptation (e.g., “I am meeting as many people, and making as many friends as I would like at university”); a 15-item Personal-Emotional subscale assessing students’ psychological and physical well-being (e.g., “I am experiencing a lot of difficulty coping with the stresses imposed on me in university”); and a 15-item Institutional-Attachment subscale that measures a student’s commitment to the institution they are attending (e.g., “Lately I have been giving a lot of thought to transferring to another university”). Items were rated on a 9-point rating scale ranging from 1 (Doesn’t apply to me at all) to 9 (Applies very closely to me), with higher scores on the scale indicating better university adjustment. The SACQ, with demonstrated strong reliability and psychometric properties, has been widely used in research of student transition to university (Beyers & Goossens, 2003; Buote et al., 2007; Krotseng, 1992; Wintre & Morgan, 2009). Furthermore, a number of studies lend credence to the criterion and predictive validity of the SACQ (e.g., Conti, 2000; Hertel, 2010; Schwitzer, Robbins, & McGovern, 1993; Wintre & Bowers, 2007; Wintre & Yaffe, 2000). The reliability of the scale in the present sample ranged from α = .90 to .92 across the three data collection periods.

Time-management (TM; Rog & Pancer, unpubl.). This 24-item scale measures students’ perceived ability to manage their time effectively. Students are asked to rate on a scale ranging from 0 (almost never) to 4 (almost always), how often they engaged in certain time-management behaviours (e.g., I outline a study plan and commit to it). These behaviours include: studying in a distraction-free environment, keeping up with course work and not leaving assignments until the last minute, following a regular study schedule and starting to study early, not putting off studying for difficult courses, planning ahead of time involvement in social activities, using a calendar/agenda to schedule due dates, attending lectures and tutorials, among others. The possible range of scores for this measure is from 0 to 88. The reliability of the scale in the present sample ranged from $\alpha = .81$ to .85 across the three data collection periods.

Statistical Analysis Overview

The repeated-measures ANOVA-based analyses can be viewed as special cases of multi-level models (MLM) (Singer & Willett, 2003). Hence, MLM can employ these same analytic strategies for simple within-subjects designs, but it also provides several advantages over ANOVA in terms of handling missing data and flexible modelling of variance-covariance structures. MLM also offers a unique data analytic strategy for within-subjects designs that is not possible when using ANOVA. Namely, MLM can be used to model individual-level trends over time, referred to as individual growth models, in which trajectories can be estimated for each participant (rather than simply average trends). An overview of MLM analysis, the advantages it offers, its prerequisite assumptions, and how those assumptions were verified are provided in Appendix A.

The current study used the longitudinal data obtained by the T2U study across the 2 cohorts and 4 data collection time points (keeping in mind the August time point included only demographic data, in other words, time-invariant variables of interest). Nested multi-level models were constructed and compared in terms of improvements in fit. These models include the time-invariant variables of gender, SES, and high school graduating GPA. Subsequently, the time-varying predictors, time-management and student perception of university support and structure, were entered in a cross-lagged design to predict the longitudinal growth curve of the students across several outcome measures, including student adjustment, perceived levels of stress, and depression symptomology (see Figure 8). The measures TM and SPUSS are referred to as process variables as they are measured at each time-point (time-variant), reflect the ongoing transaction of the individual with their environment, and are theoretically posited to have a causal relationship with the outcome measures of interest. Time was measured in terms of the academic year.

A cross-lagged design was used to address the issue of reciprocal causation, where due to the inclusion of time-varying predictors, the direction of causality becomes uncertain, such that it is unclear whether the time-varying covariate "caused" the outcome, or the outcome "caused" the time-varying covariate. Additionally, exploratory models were constructed for TM and SPUSS. These models explore the transaction between internal and external regulatory sources over time. The process or time-varying covariates of SPUSS and TM, as well as the time-invariant control variable of HGPA, were centred prior to the analysis, and therefore, the intercept terms are interpreted in the context of average covariates.

Model Selection. Model selection was started by building a simple random intercept model for calculating interclass correlation (ICC) and a simple linear growth model, followed by a model with time-invariant controls and time-variant process variables. These models were compared for fit at every step of the selection process. A full description of the model selection process is provided in Appendix A.

Model Comparison. Model comparison was accomplished using a combination of statistical tools assessing fit, including the log-likelihood (LL) ratio test, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and two R^2 measures. An alpha level of $\alpha = .01$ was chosen a priori to decide statistical significance. The first R^2 measure employed was the *marginal* R^2 and described the proportion of variance explained by the fixed factor(s) alone. The second measure used was the *conditional* R^2, which describes the proportion of variance explained by both the fixed and random factors. Both the marginal and conditional R^2 are presented for each MLM model. A full description of the model fit and R^2 indices are provided in Appendix A.

Study One: Results

The results section comprises analyses to describe inclusion decisions, attrition, and demographics of the sample. Differences between the two collection cohorts were not found to be of note in later analyses and are presented in Appendix A. Subsequently, fit indices that are used for the multi-level model (MLM) selection are described, and results from five MLMs are examined to answer the research questions. The five models include longitudinal MLMs of outcome variables (adjustment to university, perceived stress, and depression symptomology) and longitudinal MLMs of process variables (time-management and perception of support and structure).

The statistical software R, version 3.4.4, alongside R Studio, Version 1.1.442, was used for the following analyses. For a complete list of R packages used, please see Appendix A: Statistics. Furthermore, to enhance statistical verification and research reproducibility, the code that was used to produce the statistical results and graphics using R Statistical Software is made available in an addendum (Appendix C – CODE).

Inclusion Criteria and Analyses

The present study focused on the transition to university as experienced by first-year students through a longitudinal lens that examines change over time. Therefore, as part for the inclusion criteria, we were interested in students who had provided data during their first year of university (in either the fall or spring collection periods), and at least at one other occasion during their time at university. Initially, 2887 participants across the two cohorts provided demographic information prior to attending university. Data from 887 participants were not usable as they had not continued with the study after providing demographic data over the summer before attending university. Subsequently, data from 469 participants were excluded as they did not participate in at least 2 data collection points after starting university. Of the 1531 participants who met our initial inclusion criteria, those missing any of the key demographic measures such as gender, income, or high school graduating GPA were excluded from the multi-level models. After excluding 131 participants with missing demographic information, data from 1400 participants were used for the subsequent analysis.

To screen for random or careless responders, the inter-item standard deviation (ISD) was used (Marjanovic, Holden, Struthers, Cribbie, & Greenglass, 2015). Details regarding ISD are provided in Appendix A. Five participants who had high ISDs on multiple measures or on multiple measurement points were excluded from further analysis.

The final sample size prior to MLM analysis included data from 1395 participants and 3189 observations in total across time. Attributes of those included were compared to the 1492 who were excluded to discern any systemic differences in the included sample.

Analysis of the two groups revealed a significant difference between the gender proportion of participants who were included in the study and those who did not meet the inclusion criteria, with females being more likely than males to have met inclusion criteria, $\chi^2(1) = 42.73$, $p < .001$, $V = .12$, small effect size. For a breakdown of gender proportions and other demographic differences see Figure 11. There were no significant differences between the self-reported income distributions of the two groups, $\chi^2(3) = 1.96$, $p = .85$, $V = .03$. Included students had a higher average self-reported high school graduating GPA (M = 83.98) than excluded students (M = 82.31), $t(2458.9) = 6.48$, $p < .001$, $d = 0.25$, small effect size. A greater proportion of students from Guelph University were included, and a lower proportion of Memorial University students were included, $\chi^2(5) = 29.17$, $p < .001$, $V = .10$, small effect size.

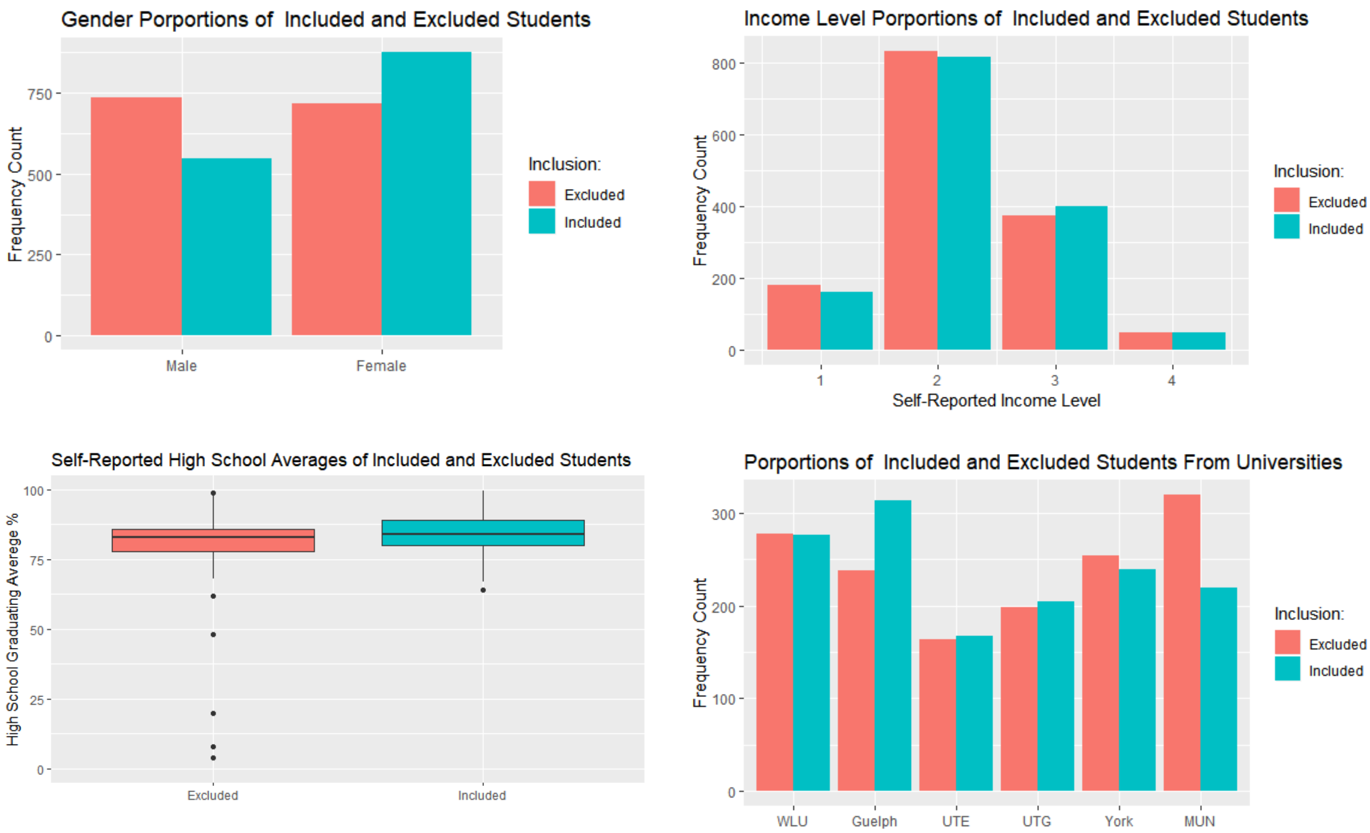

Figure 9
Comparison of attributes of the included sample and the participants who did not meet the inclusion criteria.

Attrition Analysis

Of the 1395 participants whose data were included, 618 provided data on the last data gathering occasion. The data from those students who completed the entire longitudinal study were compared to the data from the 777 participants who discontinued providing data prior to the final data collection. Attrition analysis did not reveal significant differences based on gender (χ^2 (1) = 5.02, p = .03, V = .07), income (χ^2 (3) =0.79, p = .85, V = .03), and university of attendance (χ^2 (5) = 12.71, p = .03, V = .10, small effect size). However, students who completed the study had a higher self-reported high school GPA (M = 84.7, SD = 5.95) than those who attrited (M = 83.41, SD = 5.93), t(1325) = 4.2, p < .001, d = 0.22, small effect size. For the distribution and proportion of attrition, differences see Figure 12.

Figure 10
Attrition Analyses.

Description of Sample

Data from 1395 participants with 3189 observations were used for constructing multi-level models. Participants were comprised of 60.4% female and 39.6% male students, with an average self-reported high school graduating GPA of 84.1%. Regarding SES, 12.3% of the incoming students reported to be below average, 55.8% reported to be average, 27.9% reported to be above average, and 3.9% reported their families to be well above average. Figure 13 provides the distribution of the frequency counts of these demographic attributes. The number of observations, mean, standard deviation and descriptive statistics for the three outcome measures (SACQ, PSS, CES-D) and two process measures (TM, SPUSS) are presented in Table 3, and their distribution is depicted in Figure 12.

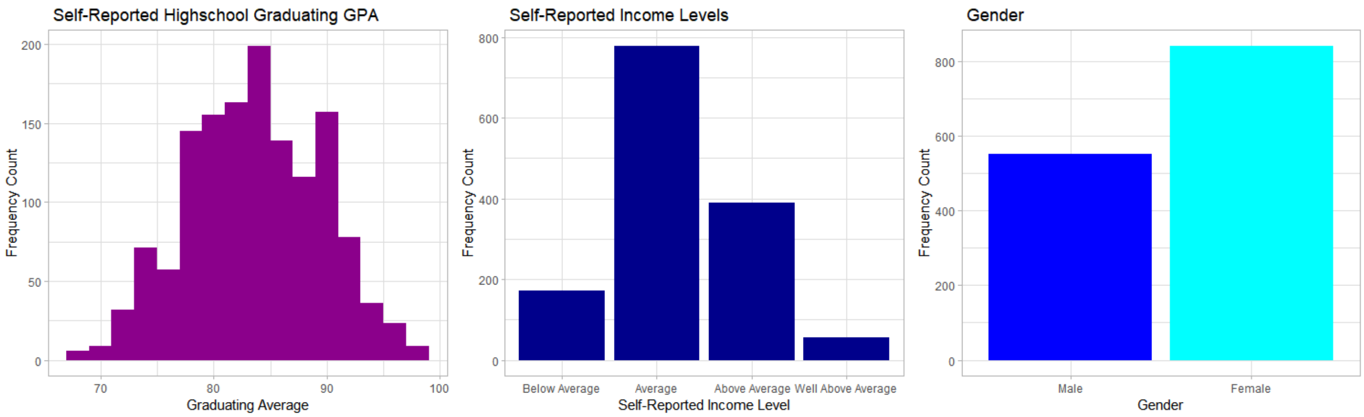

Figure 11
Demographic breakdown of the study participants.

Table 3
Summary of Descriptive Statistics for Process and Outcome Variables.

Statistic	N	Mean	SD	Min	Median	Max
Summary Statistics of Outcome Variables Spring of First Year						
SACQ Mean Scores	1,115	5.95	1.12	2.61	6.04	8.68
PSS Mean Scores	1,120	1.59	0.73	0	1.5	4
CES-D Mean Scores	1,126	0.84	0.57	0	0.7	2.85
Summary Statistics of Outcome Variables Spring of Second Year						
SACQ Mean Scores	621	5.81	1.14	2.41	5.85	8.79
PSS Mean Scores	632	1.59	0.74	0	1.5	3.75
CES-D Mean Scores	625	0.83	0.54	0.05	0.7	2.7
Summary Statistics of Outcome Variables Spring of Third Year						
SACQ Mean Scores	397	5.69	1.07	2.14	5.77	8.39
PSS Mean Scores	401	1.46	0.76	0	1.5	4
CES-D Mean Scores	402	0.76	0.54	0	0.62	2.8
Summary Statistics of Process Variables Fall of First year						
TM Mean Scores	1,272	2.24	0.66	0.32	2.23	4
SPUSS Mean Scores	1,272	6.32	1.03	2.25	6.35	9
Summary Statistics of Process Variables Spring of First year						
TM Mean Scores	1,215	2.16	0.71	0.1	2.14	4
SPUSS Mean Scores	1,215	6.26	1.09	2.7	6.25	9
Summary Statistics of Process Variables Spring of Second year						
TM Mean Scores	702	2.23	0.69	0.5	2.23	4
SPUSS Mean Scores	702	6.32	1.07	2.3	6.35	8.9

Figure 12
Distribution of process and outcome measures over the three collection time points.

Longitudinal Multi-Level Model of Student Adjustment

Empirical growth plots and fitted OLS trajectories for mean SACQ scores are depicted in Figure 13. Exploration of participant data showed reasonable linear trends and variability in slopes to consider linear models. In partitioning the random effects, the analysis was first conducted with individuals nested in university, which itself was nested in the cohort. However, variance partitioned by cohort was negligible, and given the benefit of greater power, it was removed from the model. The model selection results and comparisons are presented in Table 4. The final model selected (Model 4) has a *pseudo-*R^2 of .77, a marginal R^2 of .27, and a conditional R^2 of 0.61. The details of the model are presented in Table 5, and the model is represented by the equation:

Fixed effects: SACQ ~ Time + SPUSS + TM + Gender + Highschool-GPA+ SES
Random effects: Intercept Nested within Individuals, Nested within University

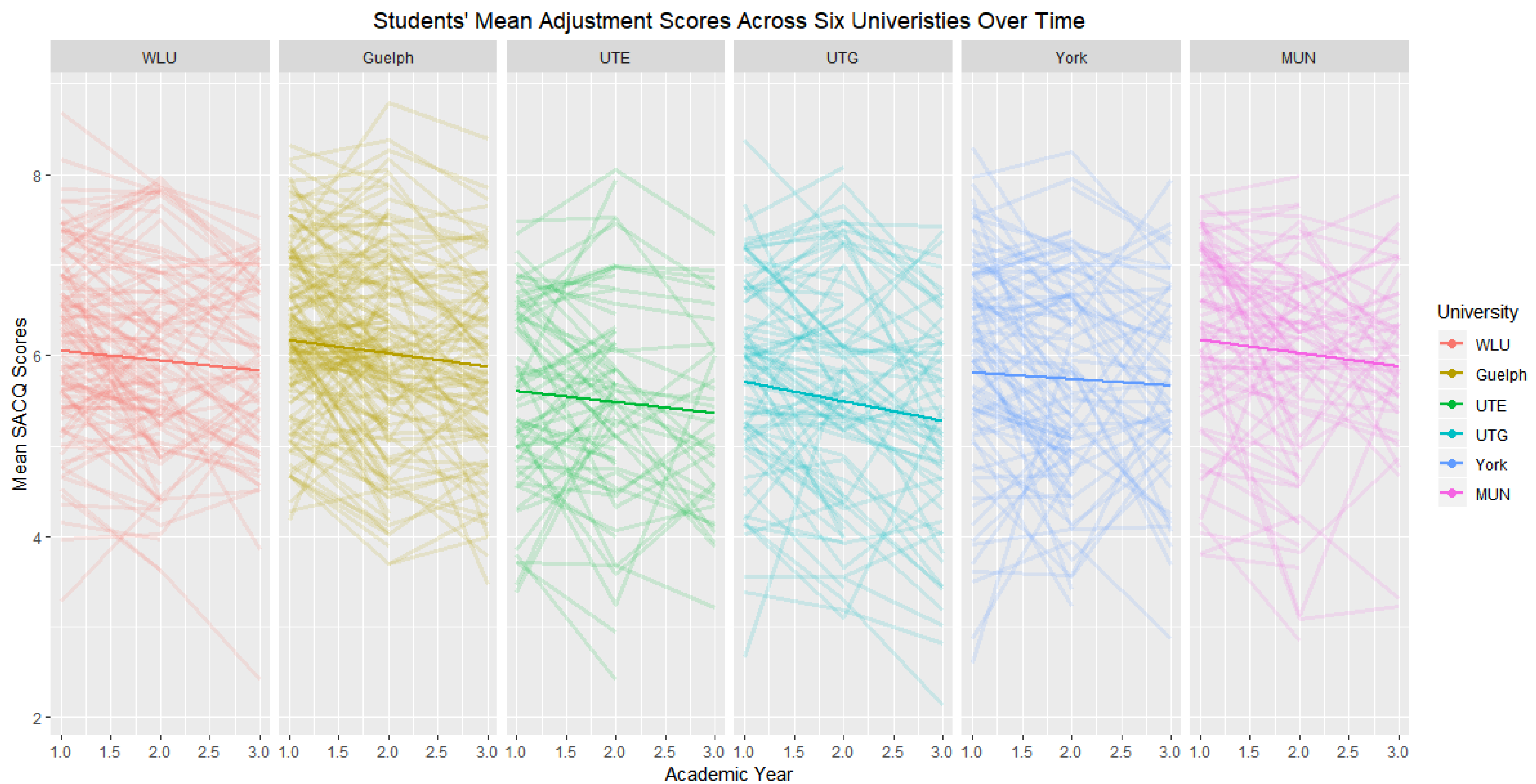

Figure 13
Empirical growth plot of mean SACQ scores over time.

Table 4

Multi-Level Model Selection of SACQ mean scores.

#	Model Name	Model Equation	-2LL	AIC	BIC	Mar. R2	Con. R2	Comments
1	Unconditional Means Model	SACQ.mean ~ 1 Random: ~1 | univ/id	NA	5963.9	5986.5	NA	NA	ICC of student scores (within university clusters) = 0.63
2	Unconditional Growth Model	SACQ.mean ~ time Random: ~time | univ/id	92.34 **	5881.5	5932.5	0.02	0.70	Proportional Reduction in individual residual when including linear growth = 0.11. Time's (i.e., slope's) random effect was negligible and removed from subsequent models.
2A	Unconditional Quadratic Growth Model	SACQ.mean ~ time + I(time^2) Random: ~time | univ/id	0.46	5883.1	5939.7	0.02	0.70	Not an improvement.
3	Conditional Model with Time-Varying Covariates	SACQ.mean ~ time + TM.mean + SPUSS.mean Random: ~1 | univ/id	304.73 **	5572.8	5612.5	0.21	0.60	Improvement over Model 2
3A	Conditional Model with Covariates Interacting with Time	SACQ.mean ~ time * SPUSS.mean * TM.mean Random: ~1 | univ/id	11.37	5569.4	5631.8	0.2	0.60	Not an improvement. Interactions are not significant.
4	**Conditional Growth Model Including Covariates and Demographics**	**SACQ.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income Random: ~1 | univ/id**	**92.85 ****	**5486**	**5542.6**	**0.27**	**0.61**	**Improvement over Model 3**
4A	Conditional Growth Model Including covariates and Interacting Demographics with Time	SACQ.mean ~ time * (agender + ahs_avg + income) + SPUSS.mean + TM.mean Random: ~1 | univ/id	3.98	5488	5561.6	0.26	0.61	Not an improvement
4B	Conditional Growth Model with Covariates Interacting with Demographics	SACQ.mean ~ time + (SPUSS.mean + TM.mean) * (agender + ahs_avg + income) Random: ~1 | univ/id	11.08	5486.9	5577.5	0.27	0.61	Not an improvement. Interaction of SPUSS and Income near significance
4C	Conditional Growth Model with Covariates, Demographics, Interaction between Income & SPUSS	SACQ.mean ~ time + SPUSS.mean * income + TM.mean + ahs_avg + agender Random: ~1 | univ/id	4.83	5483.1	5545.4	0.27	0.61	Interaction of SPUSS and Income are not an improvement.

* p<.01 ** p<.001 Final model chosen is bolded.

Table 5
MLM Results for the Outcome Measure SACQ.

Effects	**Value**	***SE***	***df***	***t***	***p***
Fixed Effects:	**Estimate**				
Intercept	5.935	0.089	1196	66.78	<.001
Time	-0.184	0.021	925	-8.57	<.001
SPUSS	0.345	0.022	925	15.93	<.001
TM	0.334	0.034	925	9.74	<.001
Gender	-0.278	0.05	1196	-5.53	<.001
High Sch. GPA	0.027	0.004	1196	6.38	<.001
SES	0.131	0.035	1196	3.72	<.001
Random Effects:	***SD***	**95% *CI***			
University Clusters:					
Intercept	0.16	[0.08,0.30]			
Individual Clusters within University:					
Intercept	0.62	[0.57,0.67]			
Error Residual	0.68	[0.65,0.72]			

Longitudinal Multi-Level Model of Perceived Stress

Empirical growth plots and fitted OLS trajectories for mean PSS scores are depicted in Figure 14. Exploration of participant data showed reasonable linear trends and variability in slopes to consider linear models. In partitioning the random effects, the analysis was first conducted with individuals nested in university, which itself was nested in the cohort. However, variance partitioned by cohort was negligible, and given the benefit of greater power, it was removed from the model. The model selection results and comparisons are presented in Table 6. The final model selected (Model 4) has a *pseudo*-R^2 of .77, a marginal R^2 of .17, and a conditional R^2 of 0.68. The details of the model are presented in Table 7, and the model is represented by the equation:

Fixed effects: PSS ~ SPUSS + TM + Gender + Highschool-GPA+ SES
Random effects: Intercept Nested within Individuals, Nested within University

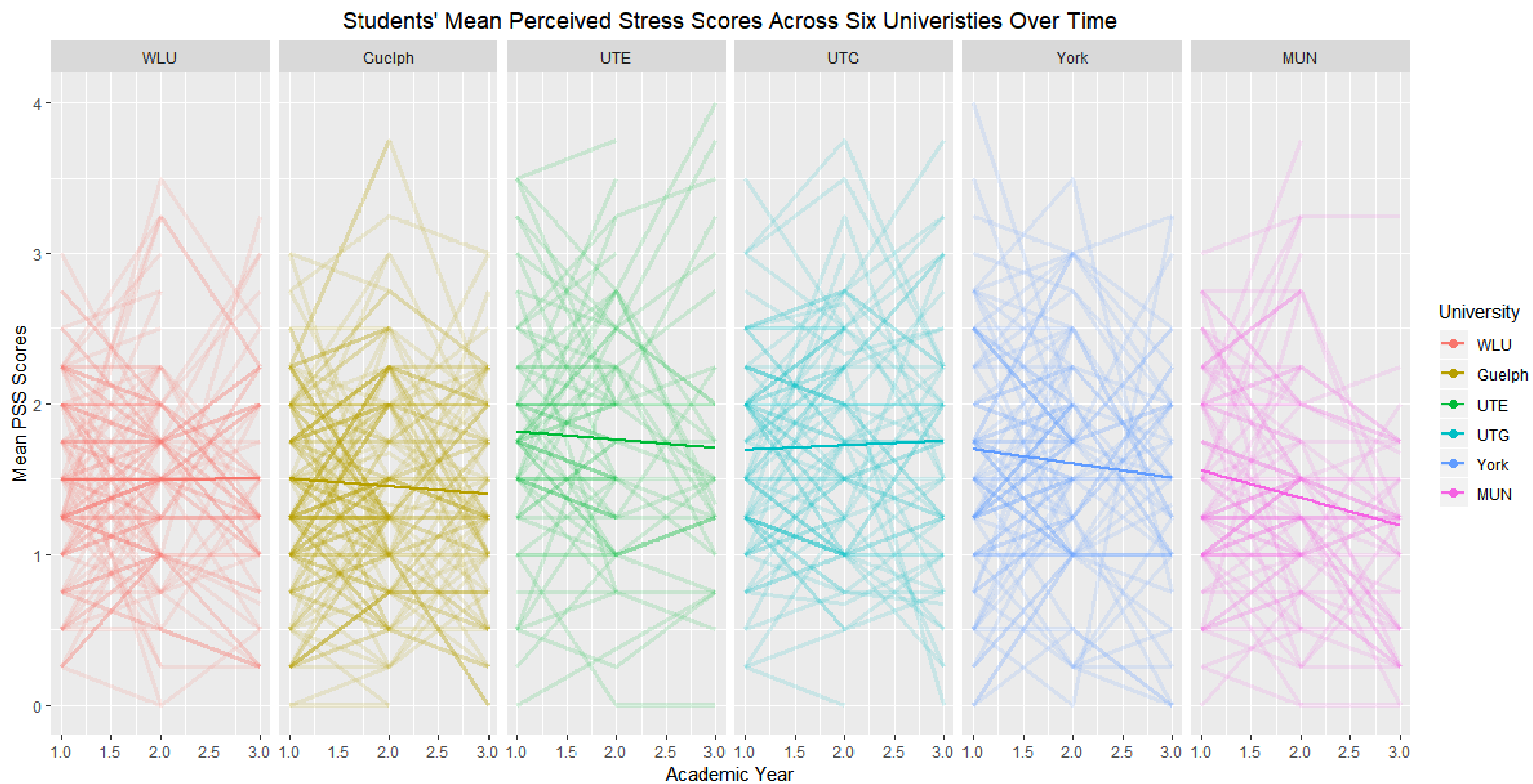

Figure 14
Empirical growth plot of mean PSS scores over time.

Table 6
Multi-Level Model Selection of PSS Mean Scores.

#	Model Name	Model Equation	-2LL	AIC	BIC	Mar. R2	Con. R2	Comments
1	Unconditional Means Model	PSS.mean ~ 1 Random: ~1 | univ/id	NA	4475.5	4498.2	NA	NA	ICC of student scores (within university clusters) = 0.49
2	Unconditional Growth Model	PSS.mean ~ time Random: ~time | univ/id	4.61	4480.8	4531.9	0	0.52	Proportional Reduction in individual residual when including linear growth = 0.02 . Time is not significantly related to changes PSS
2A	Unconditional Quadratic Growth Model	PSS.mean ~ time + I(time^2) Random: ~time | univ/id	10.78	4476.7	4533.4	0	0.53	Not an improvement. Quadratic time unrelated to changes in PSS .
3	Conditional Model with Time-Varying Covariates (Excluding Time)	PSS.mean ~ TM.mean + SPUSS.mean Random: ~1 | univ/id	207.96 **	4266.9	4300.9	0.12	0.47	Improvement over Model 1 (and 2)
3A	Conditional Model with Covariates Interacting with Time	PSS.mean ~ time * SPUSS.mean * TM.mean Random: ~time | univ/id	10.45	4274.4	4359.6	0.13	0.45	Not an improvement, and no interaction is significant
4	**Conditional Model Including Covariates and Controls**	**PSS.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income Random: ~1 | univ/id**	**77.95 ****	**4194.9**	**4246**	**0.17**	**0.47**	**Improvement over Model 3. All control variables are significant.**
4A	Conditional Model Including covariates and Interacting Controls with Time	PSS.mean ~ time * (agender + ahs_avg + income) + SPUSS.mean + TM.mean Random: ~time | univ/id	8.21	4202.7	4299.2	0.17	0.45	Not an improvement. Also no interaction is significant.
4B	Conditional Model with Covariates Interacting with Controls	PSS.mean ~ (SPUSS.mean + TM.mean) * (agender + ahs_avg + income) Random: ~1 | univ/id	8.51	4198.4	4283.5	0.17	0.47	Not an improvement. Also no interaction is significant.

* p<.01 ** p<.001 Final model chosen is bolded.

Table 7
MLM Results for the Outcome Measure PSS.

Effects	**Value**	***SE***	***df***	***t***	***p***
Fixed Effects:	**Estimate**				
Intercept	1.59	0.052	1204	30.32	<.001
SPUSS	-0.19	0.015	938	-12.16	<.001
TM	-0.17	0.024	938	-6.99	<.001
Gender	0.19	0.035	1204	5.56	<.001
High Sch. GPA	-0.015	0.003	1204	-5.19	<.001
SES	-0.091	0.025	1204	-3.69	<.001
Random Effects:	***SD***	**95% *CI***			
University Clusters:					
Intercept	0.076	[0.035, 0.16]			
Individual Clusters within University:					
Intercept	0.40	[0.36, 0.55]			
Error Residual	0.53	[0.51, 0.55]			

Longitudinal Multi-Level Model of Depression Symptomology

Empirical growth plots and fitted OLS trajectories for mean CES-D scores are depicted in Figure 16. Exploration of participant data showed reasonable linear trends and variability in slopes to consider linear models. As can be seen in Figure 12, the mean CES-D scores were not normally distributed and had a positive skew. A square root transformation was carried out on the data, and the resulting distribution was closer to normal approximation and can be seen in Figure 15.

In partitioning the random effects, the analysis was first conducted with individuals nested in university, which itself was nested in the cohort. However, variance partitioned by cohort was negligible, and given the benefit of greater power, it was removed from the model. The model selection results and comparisons are presented in Table 8. The final model selected (Model 4) has a *pseudo-*R^2 of .79, a marginal R^2 of .13, and a conditional R^2 of 0.60. The details of the model are presented in Table 9, and the model is represented by the equation:

Fixed effects: CES-D (Transformed) ~ Time + SPUSS + TM + Gender + Highschool-GPA+ SES
Random effects: Intercept Nested within Individuals, Nested within University

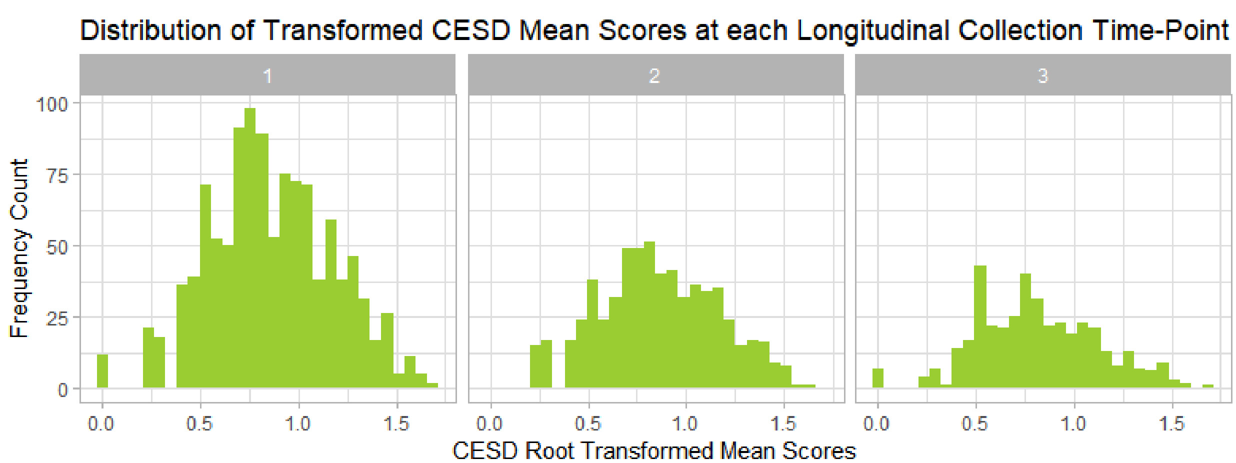

Figure 15
Distribution of Transformed CESD Mean Scores

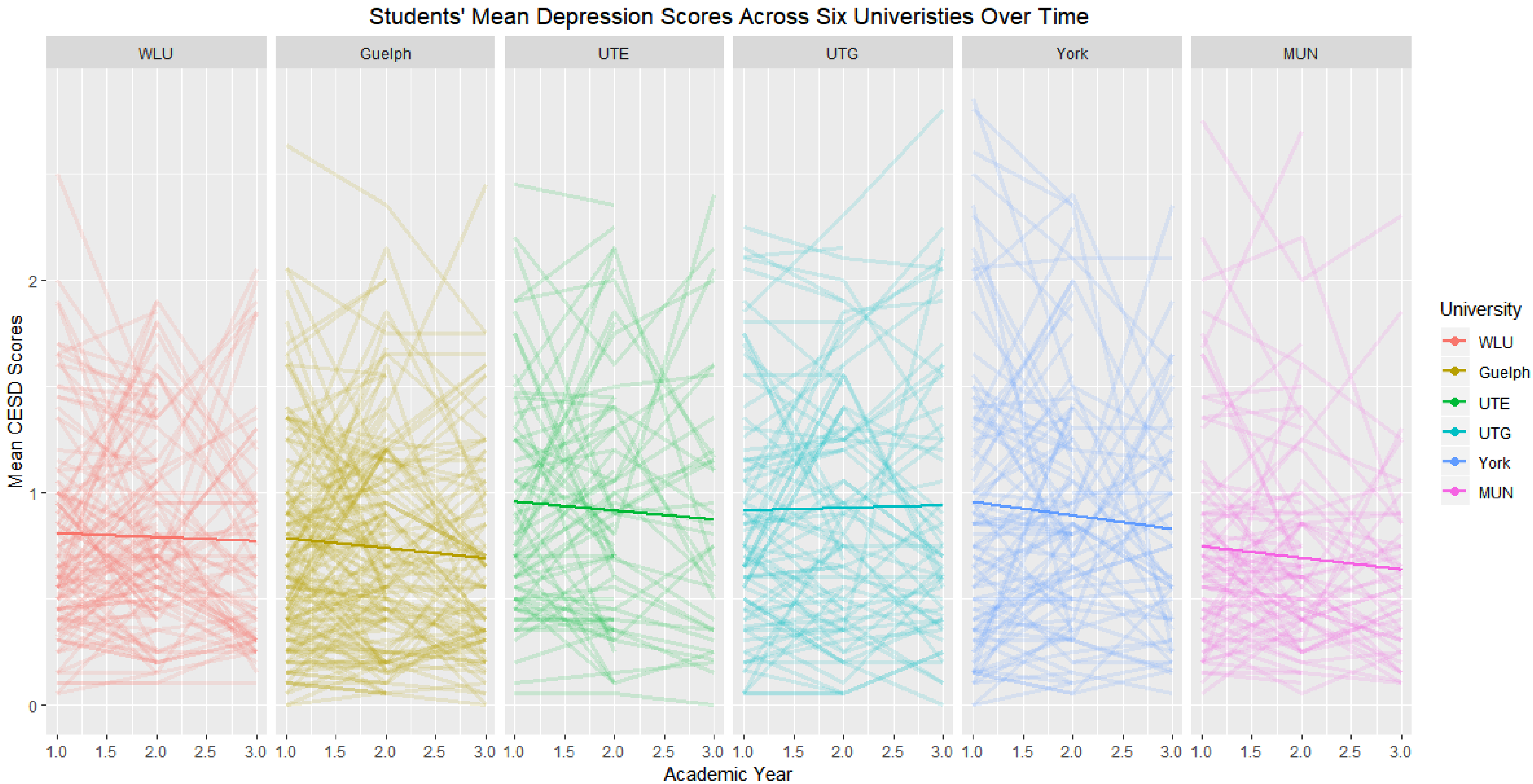

Figure 16
Empirical growth plot of mean CES-D scores over time.

Table 8
Multi-Level Model Selection of Root Transformed CES-D Mean Scores.

#	Model Name	Model Equation	-2LL	AIC	BIC	Mar. R2	Con. R2	Comments
1	Unconditional Means Model	CES-DT.mean ~ 1 Random: ~1 | univ/id	NA	604	626.7	NA	NA	ICC of ID in Universities = 0.62
2	Unconditional Growth Model	CES-DT.mean ~ time Random: ~time | univ/id	16.69 *	597.3	648.4	0	0.73	Proportional Reduction in individual residual when including linear growth = 0.17. Time's (i.e., slope's) random effect was negligible and removed from subsequent models.
2A	Unconditional Quadratic Growth Model	CES-DT.mean ~ time + I(time^2) Random: ~time | univ/id	20.97 *	595	651.8	0	0.73	Not an improvement.
3	Conditional Model with Time-Varying Covariates (Excluding Time)	CES-DT.mean ~ time + TM.mean + SPUSS.mean Random: ~1| univ/id	137.4 **	455.9	495.6	0.09	0.59	Improvement over Model 2
3A	Conditional Growth Model with Covariates Interacting with Time	CES-DT.mean ~ time * SPUSS.mean * TM.mean Random: ~1 | univ/id	8.25	455.6	518.1	0.09	0.6	Not an improvement, and no interaction is significant
4	**Conditional Growth Model Including Covariates and Controls**	**CES-DT.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income Random: ~1 | univ/id**	**60.3 ****	**401.6**	**458.3**	**0.13**	**0.6**	**Improvement over Model 3. All control variables are significant. Time is not significant**
4A	Conditional Model Including covariates and Interacting Controls with Time	CES-DT.mean ~ time * (agender + ahs_avg + income) + SPUSS.mean + TM.mean Random: ~1 | univ/id	1.41	406.2	480	0.13	0.6	Not an improvement. No interaction between controls and time is significant.
4B	Conditional Model with Covariates Interacting with Controls	CES-DT.mean ~ time + (SPUSS.mean + TM.mean) * (agender + ahs_avg + income) Random: ~1 | univ/id	5.45	408.1	498.9	0.13	0.6	Not an improvement. No interaction between covariates and controls is significant.
4C	Conditional Model Including Covariates and Controls (Excluding time)	CES-DT.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income Random: ~1 | univ/id	4.48	404.1	455.1	0.13	0.6	Not an improvement.

* p<.01 ** p<.001 Final model chosen is bolded.

Table 9
MLM Results for the Outcome Measure CES-D (Transformed).

Effects	**Value**	***SE***	***df***	***t***	***p***
Fixed Effects:	**Estimate**				
Intercept	0.89	0.022	1208	38.59	<.001
Time	-0.013	0.007	933	-2.11	.035
SPUSS	-0.069	0.007	933	-10.55	<.001
TM	-0.057	0.011	933	-5.46	<.001
Gender	0.082	0.016	1208	5.23	<.001
High Sch. GPA	-0.004	0.001	1208	-3.258	.001
SES	-0.044	0.011	1208	-3.94	<.001
Random Effects:	***SD***	**95% *CI***			
University Clusters:					
Intercept	0.027	[0.012, 0.064]			
Individual Clusters within University:					
Intercept	0.27	[0.20, 0.22]			
Error Residual	0.20	[0.19, 0.21]			

Longitudinal Multi-Level Model of Time-management

In constructing an exploratory longitudinal model for TM scores, the varying data collection time schedule was taken into account, and the measure of time was changed to semester to account for the uneven distance between time points. Semester is coded such that the intercept can be interpreted as the first collection time point in the fall of the first year (Semester = 0), the second collection time point is the spring of the first year (Semester = 1), and the last collection time point for TM was the spring of the second year (Semester = 4).

Empirical growth plots and fitted OLS trajectories for mean TM scores are depicted in Figure 17. Exploration of participant data showed reasonable linear trends and variability in slopes to consider linear models. In partitioning the random effects, the analysis was first conducted with individuals nested in university, which itself was nested in the cohort. However, variance partitioned by cohort was negligible, and given the benefit of greater power, it was removed from the model. The model selection results and comparisons are presented in Table 10. The final model selected (Model 4c) has a *pseudo*-R^2 of .91, a marginal R^2 of .08, and a conditional R^2 of 0.82. The details of the model are presented in Table 11, and the model is represented by the equation:

*Fixed effects: TM ~ SPUSS + Semester * Gender + Highschool-GPA+ SES*
Random effects: Intercept and Slope Nested within Individuals, Nested within University

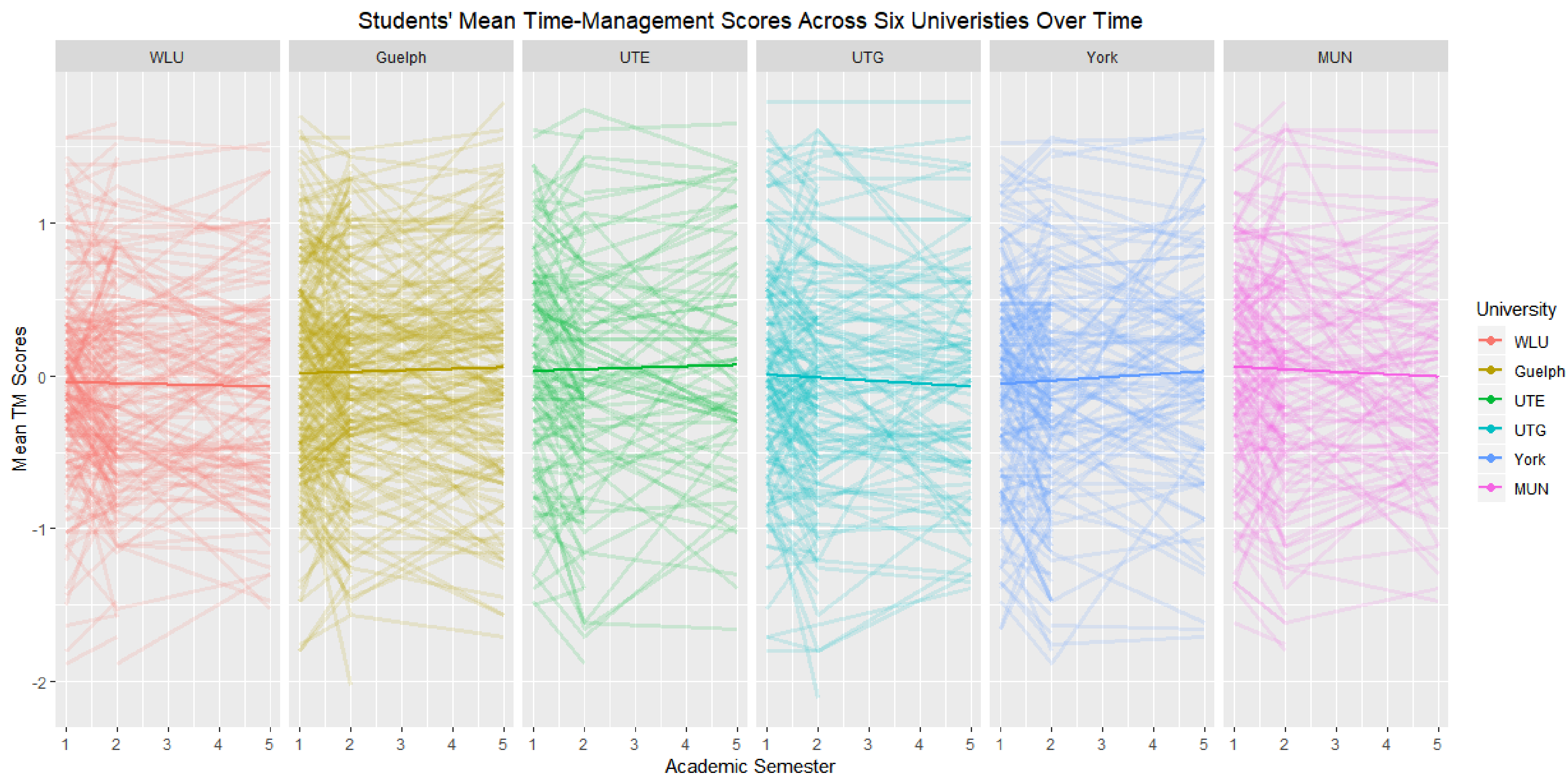

Figure 17
Empirical growth plot of mean TM scores over time.

Table 10
Multi-Level Model Selection of Time-management Mean Scores.

#	MODEL NAME	MODEL EQUATION	-2LL	AIC	BIC	MAR. R2	CON. R2	COMMENTS
1	Unconditional Means Model	TM.mean ~ 1 Random: ~1 | univ/id	NA	4922.1	4946.3	NA	NA	ICC of ID in Universities = 0.65
2	Unconditional Growth Model	TM.mean ~ semester Random: ~semester | univ/id	66.33 **	4865.7	4920.3	0	0.83	Proportional Reduction in individual residual when including linear growth = 0.75
3	Conditional Model with semester-Varying Covariate	TM.mean ~ semester + SPUSS.mean Random: ~semester | univ/id	110.41 **	4757.3	4818	0.03	0.82	Improvement over Model 2
3A	Conditional Model with Covariates Interacting with semester	TM.mean ~ semester * SPUSS.mean Random: ~semester | univ/id	3.4	4755.9	4822.7	0.03	0.82	Not an improvement
4	Conditional Model Including Covariate and Controls	TM.mean ~ semester + SPUSS.mean + agender + ahs_avg + income Random: ~semester | univ/id	89.25 **	4674.1	4753	0.08	0.82	Improvement over Model 3
4A	Conditional Model Including covariates and Interacting Controls with semester	TM.mean ~ semester * (agender + ahs_avg + income) + SPUSS.mean Random: ~semester | univ/id	10.22	4669.9	4766.9	0.08	0.82	Not an improvement, however interaction of Semester and Gender is significant
4B	Conditional Model with Covariates Interacting with Controls	TM.mean ~ semester + SPUSS.mean * (agender + ahs_avg + income) Random: ~semester | univ/id	3.72	4676.4	4773.4	0.08	0.82	Not an improvement.
4C	**Conditional Model with Covariates, Controls, and Interaction between Gender & Semester**	**TM.mean ~ SPUSS.mean + ahs_avg + income + agender * semester Random: ~semester | univ/id**	**9.08 ***	**4667**	**4751.9**	**0.08**	**0.82**	**Improvement over model 4**

* p<.01 ** p<.001 Final model chosen is bolded.

Table 11
MLM Results for the Outcome Measure TM.

Effects	**Value**	***SE***	***df***	***t***	***p***
Fixed Effects:	**Estimate**				
Intercept	-0.14	0.043	1791	-3.24	.001
SPUSS	0.11	0.01	1791	10.82	<.001
High Sch. GPA	0.021	0.003	1386	7.37	<.001
SES	0.040	0.024	1386	1.65	.1
Gender	0.17	0.035	1386	4.68	<.001
Semester	-0.031	0.008	1791	-4.01	<.001
Gender X Semester	0.029	0.009	1791	3.04	.002
Random Effects:	***SD***	**95% *CI***			
University Clusters:					
Intercept	0.022	[0.002, 0.25]			
Time	0.005	[0.001, 0.06]			
Individual Clusters within University:					
Intercept	0.58	[0.56, 0.61]			
Time	0.07	[0.06, 0.08]			
Error Residual	0.29	[0.28, 0.30]			

Longitudinal Multi-Level Model of Student Perception of Support and Structure

In constructing an exploratory longitudinal model for SPUSS scores, the varying data collection time schedule was taken into account, and the measure of time was changed to semester to account for the uneven distance between time points. Semester is coded such that the intercept can be interpreted as the first collection time point in the fall of the first year (Semester = 0), the second collection time point is the spring of the first year (Semester = 1), and the last collection time point for SPUSS was the spring of the second year (Semester = 4).

Empirical growth plots and fitted OLS trajectories for mean SPUSS scores are depicted in Figure 18. Exploration of participant data showed reasonable linear trends and variability in slopes to consider linear models. In partitioning the random effects, the analysis was first conducted with individuals nested in university, which itself was nested in the cohort. However, variance partitioned by cohort was negligible, and given the benefit of greater power, it was removed from the model. The model selection results and comparisons are presented in Table 12. The final model selected (Model 4c) has a *pseudo*-R^2 of .84, a marginal R^2 of .05, and a conditional R^2 of 0.72. The details of the model are presented in Table 13, and the model is represented by the equation:

*Fixed effects: SPUSS ~ TM + Gender + Semester * SES*
Random effects: Intercept Nested within Individuals, Nested within University

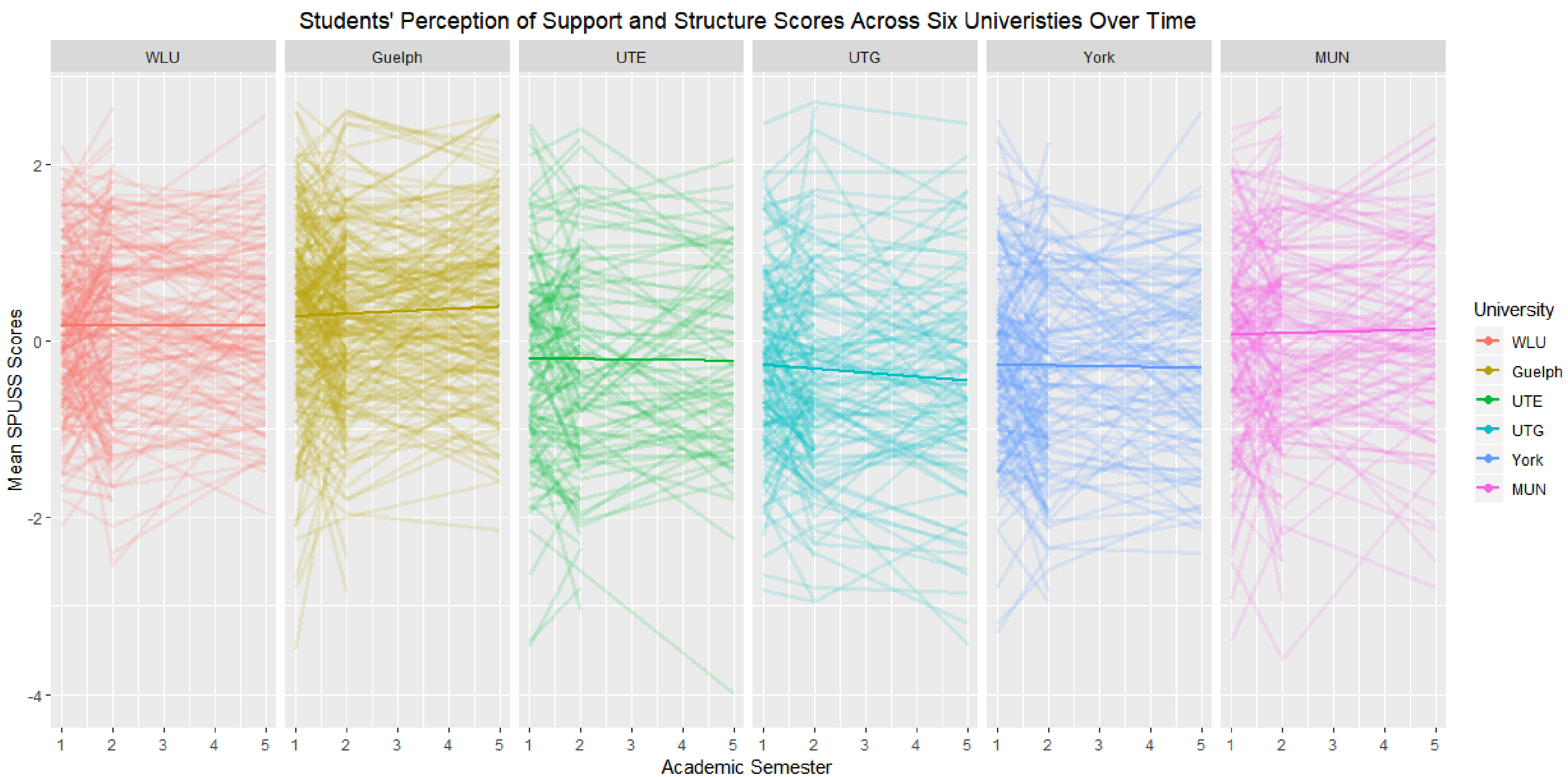

Figure 18
Empirical growth plot of mean SPUSS scores over time.

Table 12
Multi-Level Model Selection of SPUSS Mean Scores.

#	Model Name	Model Equation	-2LL	AIC	BIC	Mar. R2	Con. R2	Comments
1	Unconditional Means Model	SPUSS.mean ~ 1 Random: ~1 | univ/id	NA	8067	8091.3	NA	NA	ICC of ID in Universities = 0.65
2	Unconditional Growth Model	SPUSS.mean ~ semester Random: ~semester | univ/id	18.63 *	8058.4	8113	0	0.72	Proportional Reduction in individual residual when including linear growth = 0.08. Semester is not a significant predictor of SPUSS
3	Conditional Model with semester-Varying Covariate	SPUSS.mean ~ TM.mean Random: ~1 | univ/id	118.03 **	7932.4	7962.7	0.05	0.7	Improvement over Model 2
3A	Conditional Model with Covariate Interacting with semester	SPUSS.mean ~ semester * TM.mean Random: ~1 | univ/id	1.1	7935.3	7977.7	0.05	0.7	Not an improvement and no interaction is significant
4	Conditional Model Including Covariate and Controls	SPUSS.mean ~ TM.mean + agender + ahs_avg + income Random: ~1 | univ/id	8.19	7930.2	7978.7	0.05	0.7	Not an improvement, however Gender is a significant control
4A	Conditional Model Including covariates and Interacting Controls with semester	SPUSS.mean ~ semester * (agender + ahs_avg + income) + TM.mean Random: ~1 | univ/id	14.56	7931.8	8004.6	0.05	0.7	Not an improvement, however, interaction between income and semester is significant. Semester's (i.e., slope's) random effect was negligible and removed from subsequent models.
4B	Conditional Model with Covariates Interacting with Controls	SPUSS.mean ~ semester + TM.mean * (agender + ahs_avg + income) Random: ~1 | univ/id	2.29	7935.9	8008.7	0.05	0.7	Not an improvement.
4C	**Conditional Model with Covariate, Two Controls, and Interaction between Income & SPUSS**	**SPUSS.mean ~ TM.mean + agender + semester * income Random: ~1 | univ/id**	13.88 *	7926.5	7981.1	0.05	0.7	**Improvement over Model 3. More parsimonious than model 4a.**

* p<.01 ** p<.001 Final model chosen is bolded.

Table 13
MLM Results for the Outcome Measure SPUSS.

Effects	Value	*SE*	*df*	*t*	*p*
Fixed Effects:	**Estimate**				
Intercept	0.01	0.108	1791	0.088	.930
TM	0.332	0.028	1791	11.95	<.001
Gender	-0.14	0.051	1387	-2.80	.005
Semester	0.026	0.018	1791	1.81	.070
SES	0.034	0.038	1387	0.82	.410
SES X Semester	-0.028	0.011	1791	-2.36	.008
Random Effects:	***SD***	**95% *CI***			
University Clusters:					
Intercept	0.21	[0.13, 0.43]			
Individual Clusters within University:					
Intercept	0.82	[0.78, 0.86]			
Error Residual	0.58	[0.56, 0.59]			

Study One: Discussion

The objective of the present paper was to use a longitudinal design to test the proposed developmental-regulatory model, RESUTD, with a sample of emerging adults transitioning to university. Self-regulation in the academic context was operationalized in the longitudinal study through a questionnaire (Time-management: TM) that measured various self-initiated behaviours important to time-management at university. External regulation within the academic context was operationalized through a questionnaire (Student Perception of University Support and Structure: SPUSS) that measured students' perception of the structure and support that their university environment provided for them. The effects of entropy were conceptualized as resulting in lower levels of adjustment to university, and higher levels of mood and anxiety challenges (as measured by the SACQ, CES-D, and PSS respectively).

Demographic Predictors

Prior to examining the interplay of internal and external self-regulatory forces, the impact of time-invariant predictors including gender, past academic achievement, and self-reported socioeconomic status (SES) are explored. It was hypothesized (hypotheses 1a and 1b) that the intercept and slope of adjustment and emotional well-being outcomes would be positively impacted by higher SES and high school graduating GPA (HGPA). Gender was hypothesized to be only predictive in terms of the initial depression and stress scores, such that female students would score higher on these measures, and it was not hypothesized to impact the slope of emotional well-being outcomes. The results partially confirmed the hypotheses (1a and 1b) regarding the intercept parameters of demographic predictors.

Additionally, gender was not only predictive of depression and stress intercepts as hypothesized but it also significantly predicted the adjustment intercept. Contrary to the hypotheses made prior to the study, none of the demographic variables (SES, gender, and HGPA) contributed significantly to the slope estimate (i.e., the rate of change) in the outcome measures. In other words, they differentiated where students started their journey of adjustment and socio-emotional transition to university; however, they do not impact the rate of change in adjustment or emotional outcomes.

Gender was a significant predictor at the intercept level in all three MLM outcome models, such that female students reported a greater initial level of stress and depressive symptomatology, and lower initial adjustment levels (see Figure 19 a, Figure 20 a, and Figure 21 a). This finding is in line with prior research that has shown male students reporting higher levels of adjustment to the university during the first year (Enochs & Roland, 2006; Wintre & Yaffe, 2000).

Transition to university represents a relatively acute stressor for some students, with research showing a greater vulnerability for female students in experiencing transition as an acute stressful life event even in the presence of more available supports (Gall, Evans, & Bellerose, 2000). Curiously, research has also demonstrated that although male students may report higher levels of adjustment initially, female students are more likely to persist to graduation (Wintre & Bowers, 2007), which may in part be due to differences in help-seeking behaviours. A meta-analysis examining student attitudes towards seeking professional psychological help revealed female students as having more positive help-seeking attitudes as compared to their male counterparts, with an overall medium effect size across 14 studies (Chu, Lee, Lee, Kim, & Lee, 2010).

Socioeconomic status has been shown to impact diverse post-secondary student outcomes including adjustment, psychological well-being, and attrition (for a review see Jury, Smeding, Stephens, Nelson, Aelenei, & Darnon, 2017). Astin (1993), in his study of students' experience and attainment in post-secondary education found that students' socioeconomic status is strongly associated with various measures of student satisfaction and has a strong effect on degree completion. Subjective measures of socioeconomic status, such as perceived relative income, are reliable measures of SES and have been shown to be significantly associated with physical functioning and health outcomes in various patient populations (Nobles, Weintraub, & Adler, 2013; Quon, & McGrath, 2014).

Therefore, it is not surprising that in the present study students' perceived SES was a significant contributor to the intercept terms for all outcome models. The impact of SES on adjustment and emotional well-being trajectories for both female and male students is depicted in Figure 19 b, Figure 20 b, and Figure 21 b. Similar to SES, past academic achievement has been shown to be a predictor of student adjustment, psychological well-being, and persistence to graduation (Richardson, Abraham, & Bond, 2012; Wintre et al., 2007; Wintre & Yaffe, 2000). Similarly, in the present study, HGPA was a predictor of initial adjustment levels, depression and stress scores (See Figure 19 c, Figure 20 c, and Figure 21 c).

The combined contribution of gender, SES, and HGPA are depicted in Figure 19 d, Figure 20 d, and Figure 21 d, for student adjustment, depression scores, and stress ratings respectively. It is noteworthy that the combined effect of these pre-existing student attributes even in the context of average TM and SPUSS scores, has a dramatic consequence on the estimated trajectories of adjustment and psychological well-being. The significant impact of pre-existing student attributes behooves the university to invest in developing and implementing supports for at-risk students, including psychological interventions, to level the playing field.

Process Predictors

The time-varying predictors of TM and SPUSS, operationalizing the constructs of self-regulatory and external-regulatory resources in the academic context, as anticipated (Hypothesis 2a), impacted the trajectories of students' adjustment to university and emotional well-being outcomes. Their impact did not interact with time indicating a consistent influence on the outcome measures over time. Higher scores on TM and SPUSS predicted higher adjustment scores and lower scores on stress and depression outcomes (see Figure 22, Figure 23, and Figure 24, plots a and b).

The finding that both self-regulatory and external-regulatory resources uniquely and consistently impacted outcome measures supports the hypothesis that students with greater self-regulatory skills are less affected by the reduction in external-regulation and would experience less behavioural entropy during their transition to university (Hypothesis 2b). Therefore, a higher score on TM protects a student who is receiving less environmental support (i.e., low SPUSS) to experience normative levels of adjustment and emotional well-being.

Conversely, this finding could also be interpreted to mean that students who have not developed adequate self-regulatory skills will still transition successfully if they receive enriched external regulatory supports (Hypothesis 2b). Therefore, a higher score on SPUSS buffers a student with low TM to experience normative levels of adjustment and emotional well-being. Finally, as anticipated, students who have poor self-regulatory skills during the first year and who also receive inadequate external-regulation (i.e., low on both TM and SPUSS), experience adjustment and emotional difficulties. See plot c on Figure 22, Figure 23, and Figure 24 for the illustration of Hypotheses 2a and 2b.

Development and Transaction of Self-Regulatory and External Regulatory Resources

The exploratory MLM models developed to examine the trajectory of SPUSS and TM revealed both demographic predictors as well as an association between the process measures. Note that since a cross-lagged design was not used, a significant relationship between the process measures can be interpreted as an association. In terms of SPUSS, male students reported a greater level of environmental support and structure, which corresponds to their higher level of adjustment as compared to female students. The significant interaction between SES and time can be interpreted as indicating that students with higher socioeconomic resources progressively perceive less support from the university environment during the course of their studies. Exploring the cause of this interaction is beyond the purview of the current study and could be investigated in future research.

In the case of students' internal regulatory resources (i.e., TM), high school graduating GPA was a significant positive predictor. This finding mirrors the significance of HGPA in predicting the outcome measures of emotional well-being and adjustment and points to the importance of time-management skills for any intervention designed for this at-risk student group. Time was negatively related to TM, which would be expected in the case of increasing academic demands (i.e., expanding behavioural space) as students progress through their undergraduate program.

Female students had both a higher initial level of TM, and a positive slope (due to the interaction of gender and time), indicating that their self-reported time-management skills increased as they progressed through the early semesters as compared to their male peers. This finding may partially account for the discrepancy in prior findings, mirrored in the present study, of male students having higher initial adjustment and lower psychological challenges, yet persisting to graduating at a lower rate than their female counterparts (Wintre & Bowers, 2007).

Finally, the results provided support for the hypotheses (3b) that students develop their self-regulatory skills over time if provided external scaffolding in the form of support and structure from the university given the significance of SPUSS in predicting TM scores. However, due to the associative nature of this exploratory examination of TM and SPUSS the direction of causality cannot be assumed, and an experimental intervention would be required to examine this hypothesis further.

There is evidence that first-year students are particularly vulnerable to ill effects of poor adjustment, with the majority of students who leave university doing so during their first year (e.g., Gaither, 1992; Wintre & Morgan, 2009). The first year of university is therefore especially important where issues of attrition are concerned (Noel, 1985). Using the estimates derived from the MLM results of the three outcome measures, a hypothetical example is constructed to showcase the impact of early intervention on the adjustment, depression, and stress trajectories of at-risk students. Plots ‘d’ on Figure 22, Figure 23, and Figure 24 illustrates the hypothetical case of two groups of at-risk students (with low SES, HGPA, and internal self-regulatory resources) who are transitioning to university. One group is shown to be receiving extra support and scaffolding from the university with targeted intervention to build up their internal regulatory resources, and they are contrasted with a second group who receive no such support. The projected trajectory of the at-risk students who are given enhanced supports improves over time and reaches the overall sample average. Should it be the case that external scaffolding can enhance internal self-regulatory resources, as the data suggest, it would be important to explore early interventions that could help students develop their self-regulatory resources.

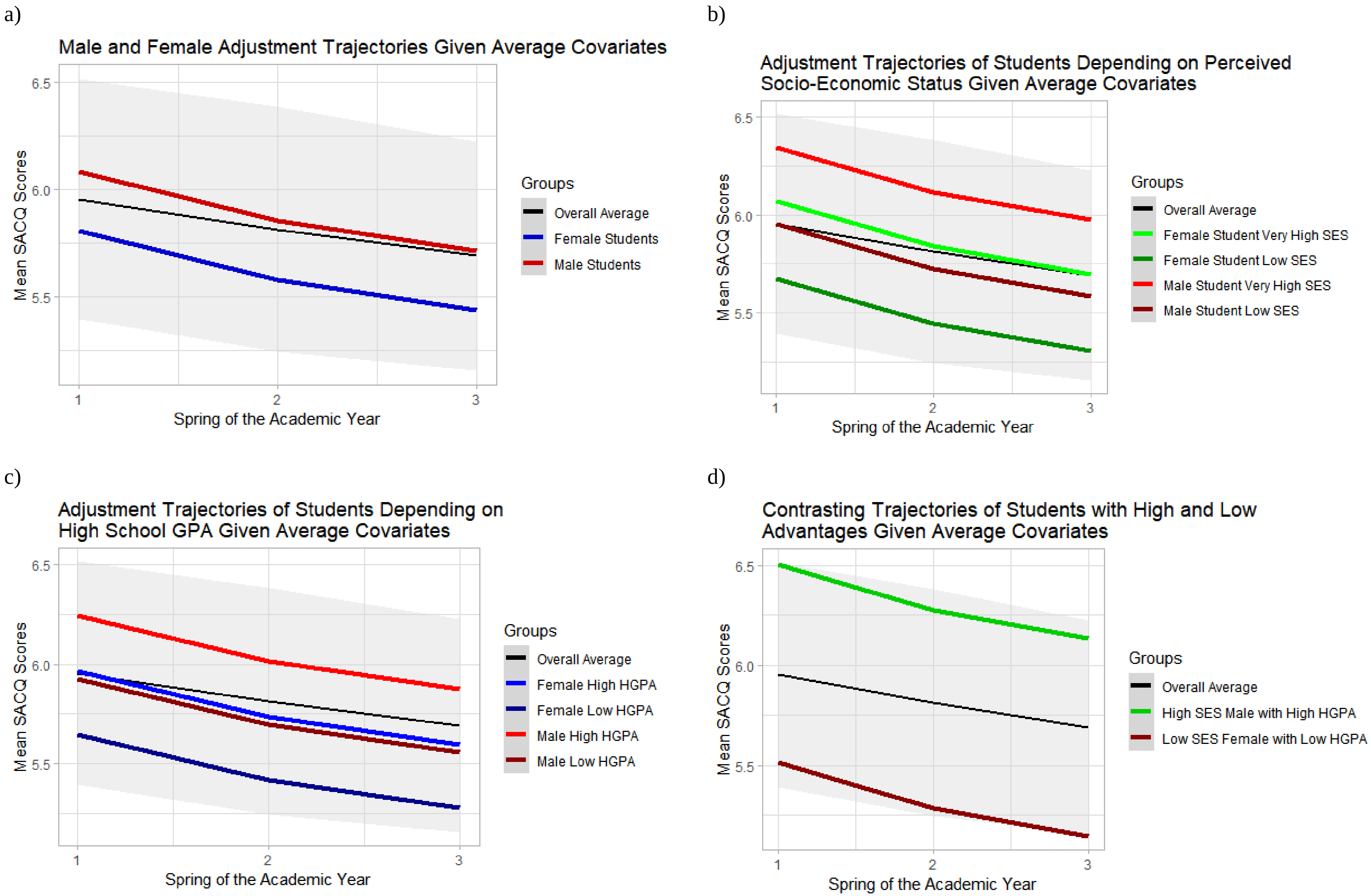

Figure 19. The estimated impact of demographic and control variables, including a) gender, b) SES (only the lowest and highest levels illustrated), c) HGPA, and d) their most disparate combination, on adjustment scores given average covariates. Empirical mean adjustment scores and 1SD band (black line and shaded area) are depicted to demonstrate the magnitude of the effects. "High" and "Low" refer to 1SD above or below the mean respectively.

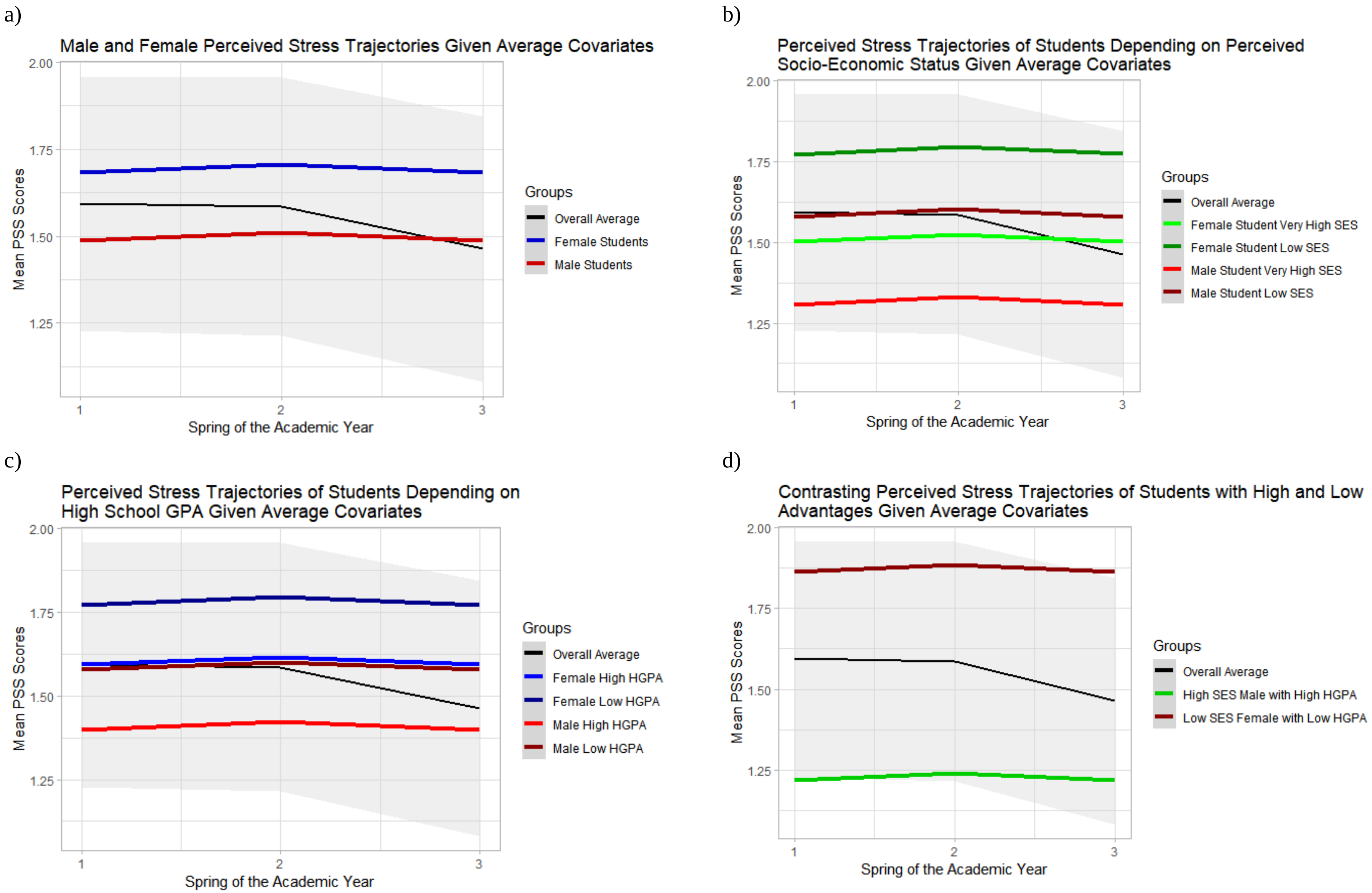

Figure 20. The estimated impact of demographic and control variables, including a) gender, b) SES (only the lowest and highest levels illustrated), c) HGPA, and d) their most disparate combination, on stress scores given average covariates. Empirical mean adjustment scores and 1SD band (black line and shaded area) are depicted to demonstrate the magnitude of the effects. “High” and “Low” refer to 1SD above or below the mean respectively.

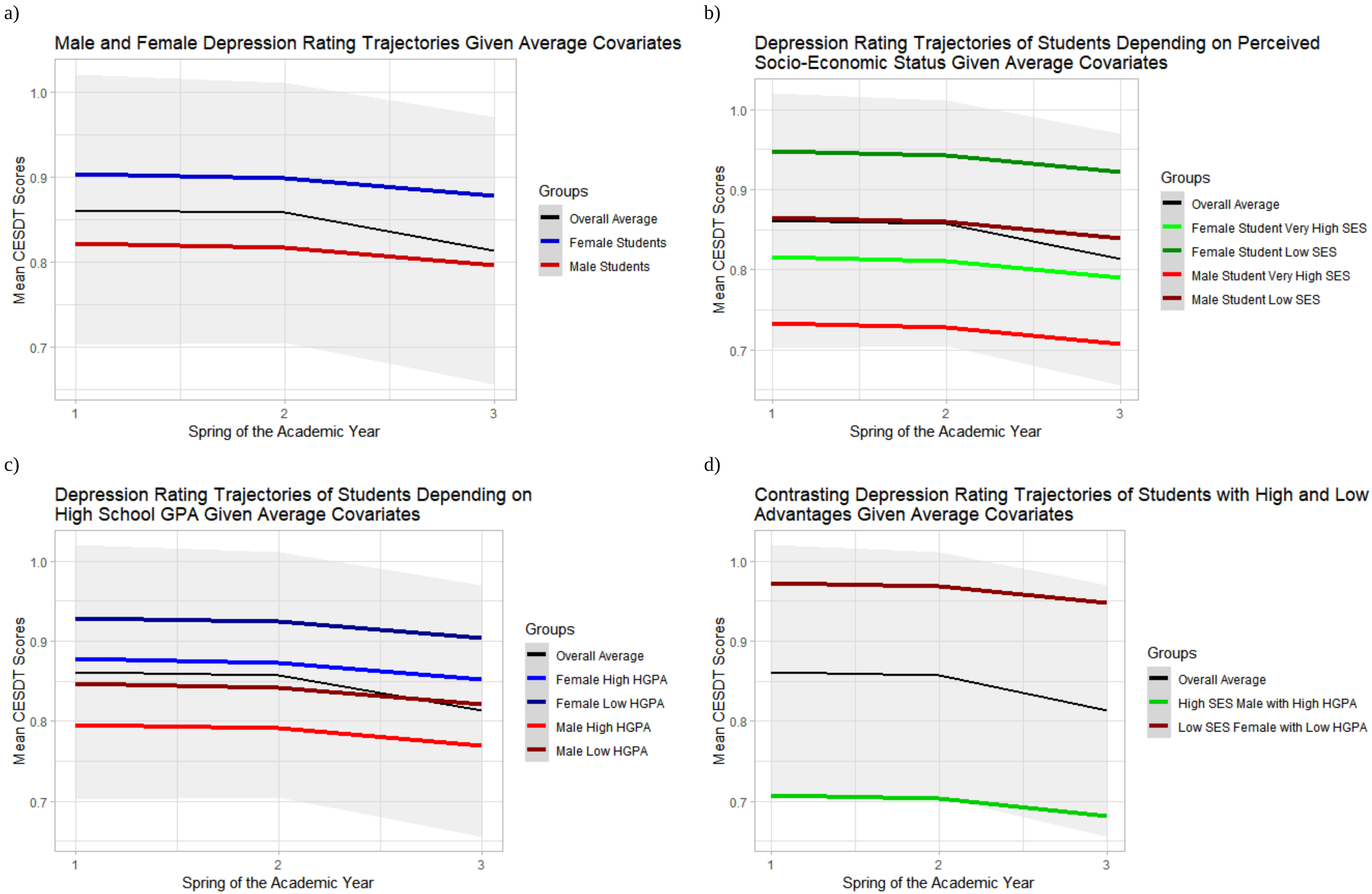

Figure 21. The estimated impact of demographic and control variables, including a) gender, b) SES (only the lowest and highest levels illustrated), c) HGPA, and d) their most disparate combination, on depression scores given average covariates. Empirical mean adjustment scores and 1SD band (black line and shaded area) are depicted to demonstrate the magnitude of the effects. “High” and “Low” refer to 1SD above or below the mean respectively.

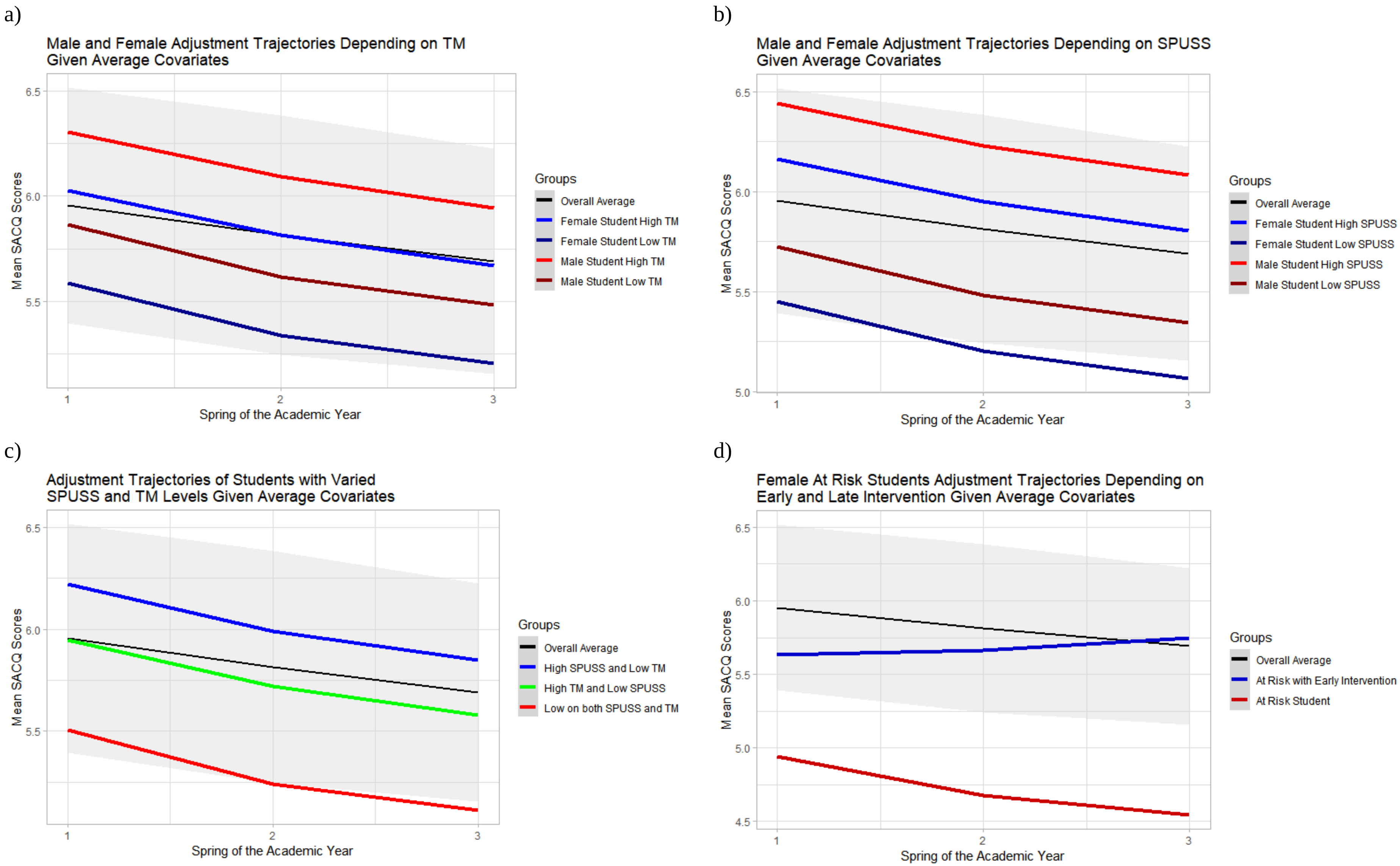

Figure 22. The estimated impact of time-varying predictors, including TM (a), and SPUSS (b), as well the combination of their varying levels (c), on adjustment trajectories. The hypothetical impact of an intervention enhancing SPUSS and TM in ameliorating students' adjustment trajectory (d). Empirical mean adjustment scores and 1SD band (black line and shaded area) are depicted to demonstrate the magnitude of the effects. "High" and "Low" refer to 1SD above or below the mean.

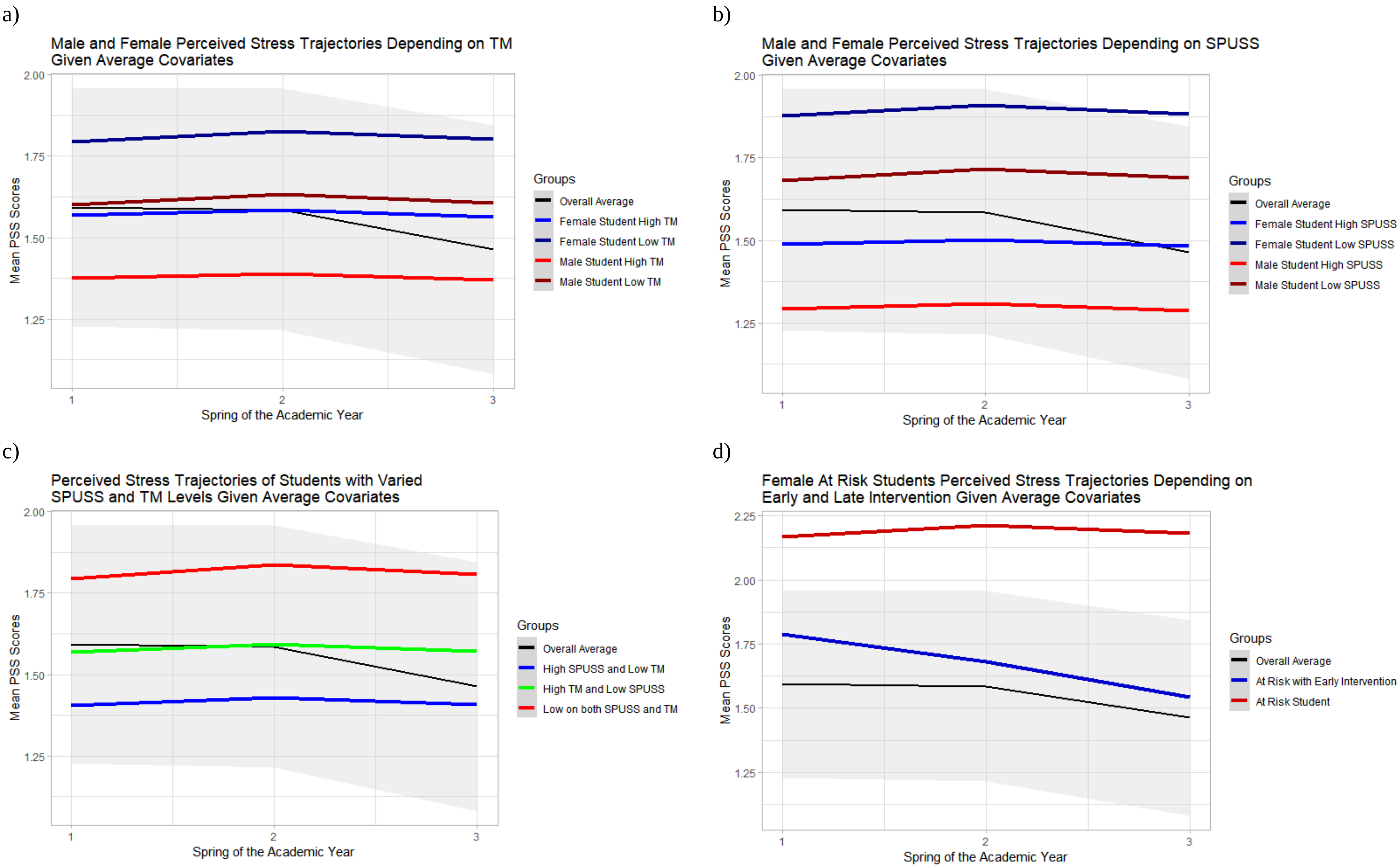

Figure 23. The estimated impact of time-varying predictors, including TM (a), and SPUSS (b), as well the combination of their varying levels (c), on stress ratings trajectories. The hypothetical impact of an intervention enhancing SPUSS and TM in ameliorating students' stress rating trajectory (d). Empirical mean stress rating scores and 1SD band (black line and shaded area) are depicted to demonstrate the magnitude of the effects. "High" and "Low" refer to 1SD above or below the mean.

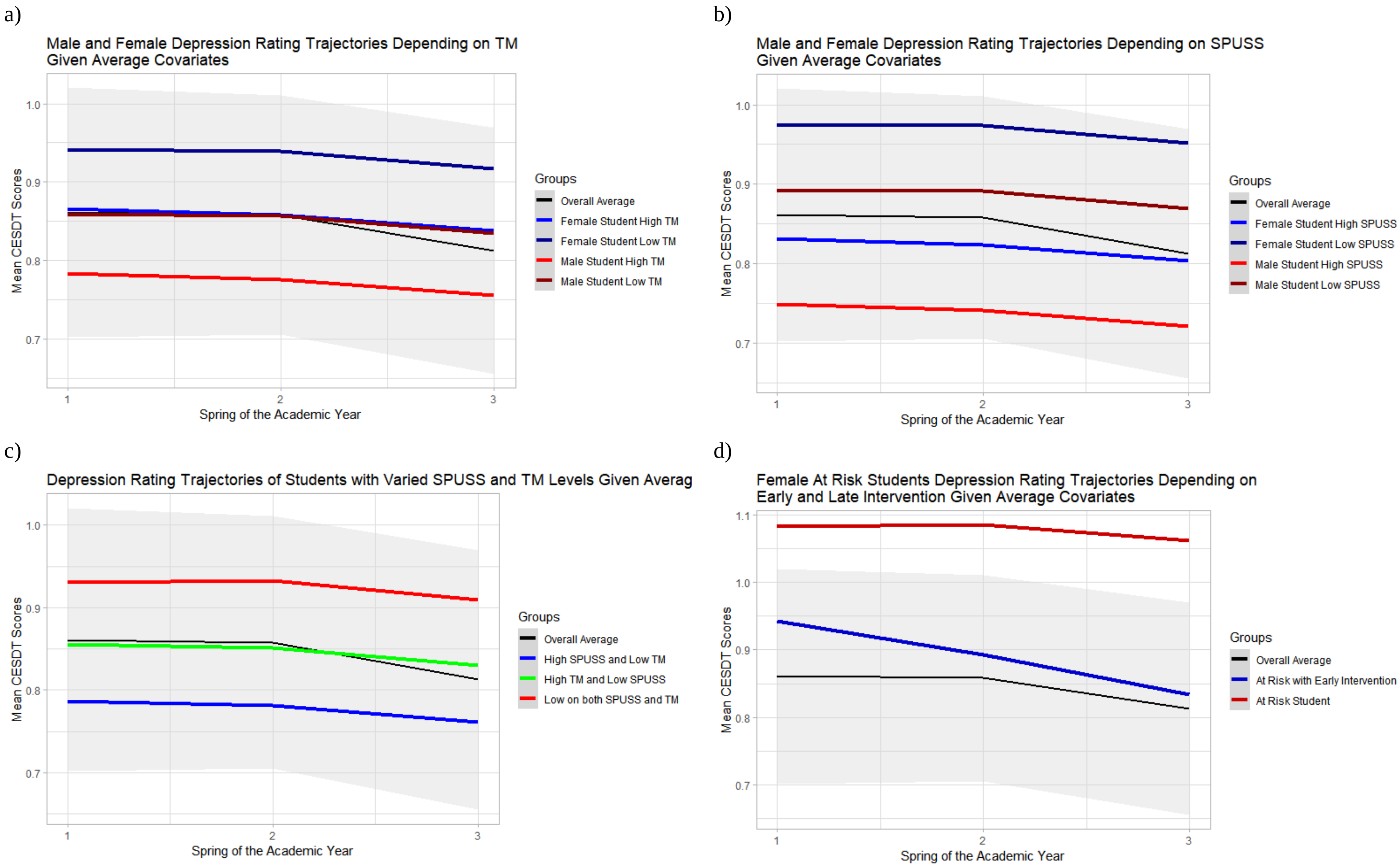

Figure 24. The estimated impact of time-varying predictors, including TM (a), and SPUSS (b), as well the combination of their varying levels (c), on depression score trajectories. The hypothetical impact of an intervention enhancing SPUSS and TM in ameliorating students' depression score trajectory (d). Empirical mean depression scores and 1SD band (black line and shaded area) are depicted to demonstrate the magnitude of the effects. "High" and "Low" refer to 1SD above or below the mean.

Study Two: Randomized Trial of a Self-Regulation Intervention Workshop for First Year Students

Having explored the development and transaction of self-regulation and external regulation in emerging adults during the transition to university, we proceeded in the second study to the question of devising an effective intervention for supporting this development.

Emerging adults today, who comprise the majority undergraduate university populations (Arnett, 2014), often juggle a full and demanding schedule in which time is divided between courses, homework, extra-curricular activities, socializing, and part-time jobs, among many other activities (Fosnacht, McCormick, & Lerma, 2016).

Concomitant with this multitude of roles and responsibilities that today's emerging adults juggle during their transition to university, there has been a general decline in the number of hours that they spend studying outside of the classroom. Babcock and Marks (2011) examined the time use of undergraduate students in the United States from 1961 to 2003, and they estimate that full-time students spent 40 hours per week studying and attending class in 1961, but only 27 hours per week in 2003.

More recent research using time diaries kept by undergraduate students revealed that on average, students spent about the same amount of time studying for courses (about 12 hours per week) as they do actually attending courses each week (Hanson, Drumheller, Mallard, McKee, & Schlegel, 2010). By comparison, students indicated that the greatest amount of personal time is spent in some form of communication, spending about 14 hours each week texting and roughly six hours talking on the phone (Hanson et al., 2010). Other researchers also confirm that students have changed how they allocate their time because of these busy schedules and commitments, from spending between two to three hours a week on coursework for every one credit hour during the decades from 1960s to 1990s, to a ratio of one hour of coursework per week for every one credit hour of class in the new millennium (Fosnacht et al., 2016, Manthei & Gilmore, 2005; Nonis, Philhours, & Hudson, 2006). The aforementioned studies highlight the contention that students are not spending sufficient time on coursework outside of class. This trend of spending less time on academic work is rather alarming given the importance of out-of-class work for learning and academic performance (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2011).

Students' busy schedules combined with commitments outside of the academic setting, such as employment, make the value of strong time-management skills even more apparent. For example, Nonis & Hudson (2010) investigated the influence of a set of behaviours they labelled "study habits" using a scale that examined students' ability to schedule (e.g., scheduling regular review periods) and ability to concentrate (e.g., ability to pay attention in class). They found that study habits moderated the relationship between study time and student performance. Similarly, Lahmers and Zulauf (2000) studied the relationship between time spent studying, the amount of time spent in class, and time-management ability in relation to grade point average (GPA). They found that although time spent studying was positively related to GPA, the association of time-management ability with GPA in their regression model was of a higher magnitude. Time-management skills are important for students' academic success, particularly in the first year as they transition to university. Both research and feedback from first-year instructors indicate that this is an area of weakness for most first-year students, which often leads to a failure to successfully meet the higher demands of university courses (Claessens et al., 2007; Murtha, personal communication June 5, 2016).

Given the importance of time-management skills to student success, the Vice Dean of Teaching in the Faculty of Health at York University invited a proposal for a time-management intervention for students in their first year of study. A time-management intervention that was inspired by Sameroff's regulatory model, and which focused both on enhancing the students' ability to structure their environment and on strengthening their internal self-regulatory resources was carried out during the winter of 2017. The present study evaluates this time-management intervention.

The intervention was designed to teach students skills such as avoiding multitasking, pre-planning their studying schedule, and structuring their digital and physical environment to avoid distractions. Students completed a battery of questionnaires prior to the workshop and attended one of four workshops, two of which were the intervention condition unbeknownst to the students. Students were randomly assigned to groups. Students in both groups completed questionnaires at the end of the term, and a majority of the students provided permission to the researchers to obtain their final grade in the course.

Our first hypothesis was that students who received the time-management intervention, as compared to those in the control condition, would have improvements in their self-reported time-management skills and their adjustment to university, have lower levels of anxiety and depression, and have higher grades at the end of the term. Our second hypothesis, which is derived from the model depicted in Figure 6, is that the intervention would be more effective in creating change in self-reported time-management skills and adjustment levels for those students with lower self-regulatory skills at the beginning of the term, than for those with well developed self-regulatory skills. Finally, we posited that students' graduating high school average would interact with the intervention condition in predicting their course grade, such that students with lower high school grade point will receive greater benefit from the intervention.

Research Informing Intervention Design

We designed the intervention, informed by the RESUTD theoretical framework, to enhance the students' self-regulatory skills and their capacity to structure their environment. We chose specific elements of the intervention based on the information obtained from the recent literature on challenges faced by students in regulating their behaviour, with a particular focus on academic behaviours. The intervention tackled specific time-management issues that we encountered in the literature, such as multi-tasking behaviours and planning studying time, which are expounded below.

Multitasking in the Academic Context. With many of the newer technologies and platforms used for social communication and personal entertainment in the last decade, and greater availability of laptops, tablets, and smartphones, it is not surprising that multitasking is becoming more common in academic settings (Jacobsen & Forste, 2011). This trend of increased multitasking is particularly true for students who are in their first year of university, which is a critical period that affords the greatest challenges during their transition to university, with upwards of 20% of students not continuing to their second year of study at the same institution (Finnie & Qiu, 2009). Research by Judd and Kennedy (2011) showed that post-secondary experiences may temper students' propensity to multitask. They found that first-year students were more likely to multitask than second-year students. Using time-diaries Jacobsen and Forste (2011) tracked multi-tasking in first-year students, finding that the majority of students use electronic media for multitasking, with a negative relationship between the use of various types of electronic media and first semester grades.

According to a multitude of research findings, multi-tasking by students has severe negative ramifications both in terms of their learning and academic outcomes. Studies have shown that multitasking with technology, specifically social platforms such as instant messaging, decreases efficiency and productivity in an academic setting (Bowman et al., 2010). In an experiment looking at reading, participants who were told to engage in instant messaging while performing the reading task took significantly longer to complete the task, and the more time participants reported spending on messaging, the lower their reading comprehension scores. They also found that the more time participants reported spending on instant messaging, the lower their self-reported GPA (Fox, Rosen, & Crawford, 2009). Similar results are obtained by other researchers who have examined multitasking in the classroom. Their findings reveal that when students have access to laptops and cell phones in the classroom, they often engage in distractive multitasking behaviours, which were negatively associated with self-reported understanding of course material, and overall course performance (Ellis, Daniels, & Jauregui, 2010; Fried, 2008; Rosen et al., 2011; Wood et al., 2012; Wurst et al., 2008)

The negative effects of multitasking are not limited to in-class learning, as students often engage in similar behaviours while studying outside of the classroom. Calderwood, Ackerman, and Conklin (2014) used surveillance cameras and other tracking technology to examine multitasking among college students engaged in a three-hour solitary study/homework session. They found that, on average, students encountered 35 distractions during three hours of independent study and were engaged with these distractions for approximately 26 minutes. Similarly, using a large survey of college students examining multitasking behaviours, Junco and Cotton (2012) discovered that students reported frequently searching for content not related to courses, using Facebook, emailing, talking on their cell phones, and texting while doing schoolwork. Further analysis revealed that using social media and texting while doing schoolwork were negatively associated with overall college GPA.

Finally, the detrimental effects of multitasking on learning and overall academic performance are not constrained to the individual actor but affect other students who may sit close to them during the lecture. Sana, Weston, and Cepeda (2013) found that students who multitasked on a laptop during a lecture scored lower on a test compared to those who did not multitask. Furthermore, participants who were in direct view of a multitasking peer scored lower on a test compared to those who were not. In other words, students sitting nearby a multi-tasker also underperformed, despite actively trying to focus on the lecture

The Downside of Multitasking. We often refer to multitasking as carrying out simultaneously two or more cognitive or information processing activities, such as perceiving images and sounds, processing or producing language, making decisions, planning, or choosing a particular behavioural response (Fischer & Plessow, 2015). While many people erroneously assume that they are capable of multitasking without loss of efficiency or effectiveness (Kirschner et al., 2006), there is substantial evidence that shows frequently switching between tasks leads to poorer performance. For example, across a number of studies researchers have found that both learning and performance on tasks while multitasking, as compared to serially completing them, takes longer and leads to a reduction of productivity by upwards of 40-percent (Rosen, & Crawford, 2009). Even the simplest and highly trained cognitive operations are subject to substantial processing limitations when combined with another task (Levy, Pashler, & Boer, 2006). There is also evidence that individuals who repeatedly multi-task do not become better at task-switching, and may even incur deficits in other cognitive processing domains. Ophir and colleagues (2009) found that heavy media multitaskers were more susceptible to interference from irrelevant environmental stimuli leading to the surprising result that they performed worse on a test of task-switching ability, likely due to reduced ability to filter out interference from the irrelevant task set.

Due to the limitations of the human cognitive processing abilities, people are not capable of true multitasking. Most researchers explain typical performance decrements in multitasking with a structural capacity limitation, a "processing bottleneck" at which certain cognitive processes proceed serially (Fischer & Plessow, 2015). Instead, what we engage in when attempting to carry out two or more tasks that demand conscious attention at once is "task-switching," where attention is switched rapidly between two tasks that are serially processed (Pashler 1994; Dux, Tombu, Harrison, Rogers, Tong, & Marois, 2009). Task-switching involves the extraction of attentional and cognitive resources from one task, and their redeployment towards a second task. This process is inherently sequential (i.e., linear); however, when done rapidly or repeatedly can give rise to the subjective feeling of multi-tasking.

Many researchers believe that the cognitive processes subject to the most severe form of bottlenecking are the planning of actions, retrieval of information from memory, and encoding information for later recall. Performing two or more of these tasks at the same time typically results in severe performance costs in terms of increased response latencies and error rates (Dux et al., 2009; Fischer & Plessow, 2015). Although capacity limitation arises at core processing stages when attempting to multitask (e.g., planning, response selection, encoding) leading to serial processing, peripheral processing stages of two tasks following the main processing (e.g., surface level processing of perception, carrying out a decided or planned motor response) can proceed in parallel (Fischer & Plessow, 2015).

Why is it hard to stop multitasking? Given the negative consequences of multi-tasking, why are the new generation of students engaging in it even more? Facebook, Twitter, Instagram, and other social media, because of continuous stimulus novelty, social relevance, and self-disclosure (i.e., status updates and tweets) are rewarding to the minds of the students (Giedd, 2012; Tamir & Mitchell, 2012) and, much like the marshmallows in Michelle's (1989) famous delay of gratification studies, students have to exert self-control to override the impulse to indulge in them. For example, a series of experiments using fMRI imaging revealed that disclosing information about oneself activates the reward pathway (the nucleus accumbens and the ventral tegmental area), which is the same mechanism for the generation of the pleasure sensation involved in other activities such as eating food or having sex (Tamir & Mitchell, 2012).

Ego depletion and self-restraint from multitasking. An important topic in self-regulation is the proper allocation of limited self-control, or "will power" resources, including the ability to sustain attention and persevere at a difficult task. Ego depletion refers to the idea that self-control and other mental processes that require focused conscious effort rely on energy that can be used up. When this limited resource is depleted, an activity that requires self-control (such as delaying gratification) is impaired. In other words, an individual's willpower has a limited capacity that can be drained when repetitively used and over-relying on it as a self-control strategy may not be successful (Baumeister et al., 1994). In experiments testing the effects of ego depletion, participants are administered consecutive regulatory tasks. The first regulatory task is expected to deplete regulatory strength rendering further acts of self-control less likely to succeed. For instance, Vohs and Heatherton (2000) found that dieters ate significantly more when instructed to suppress emotional responses to a video clip, compared to when they could respond naturally. The findings of depletion have been replicated several times with individuals unable to maintain self-regulatory behaviour in the second instance across a variety of behavioural domains (Baumeister, Bratslavsky, Muraven, & Tice, 1998; Finkel & Campbell, 2001; Muraven et al., 1998; Vohs & Heatherton, 2000; Vohs & Schmeichel, 2003).

By taking into account the evidence for ego depletion, and the rewarding nature of common multitasking distractors that students engage in, such as checking Facebook or sending instant messages, researchers can better understand why students have difficulty resisting the urge to multitask at the lecture or when doing homework. To help students confront these challenges, the intervention involved psychoeducation about these topics and tools that students could use to structure their digital environment (such as internet blockers).

Decision fatigue. The last component of the intervention built on the concept of ego depletion to provide students with ways of pre-planning some of their academic activity, particularly how they spend their time on campus. Research has shown that making decisions depletes the same resource used for self-control and active responding (Vohs et al., 2008). Across various studies, Vohs and colleagues found that making choices led to reduced self-control (i.e., less physical stamina, reduced persistence in the face of failure, more procrastination, and less quality and quantity of arithmetic calculations). These findings suggest that students may sometimes encounter difficulties starting to study because of the number of decisions involved in planning the studying activity (location, topic, length of time, etc.). Therefore, pre-planning their studying sessions can prove beneficial to students by helping them not tax their regulatory resources prior to the main academic activity (Rau & Durand, 2000). The intervention presented to the students the importance of pre-planning a portion of their studying time and relying on routines to form studying habits. Students were also introduced to the Pomodoro Technique (PT), a time-chunking methodology that provides a routine structure for focused work and taking breaks (Cirillo, 2006). PT is a time-management method that uses a timer to break down work into intervals, traditionally 25 minutes in length, separated by short breaks (Cirillo, 2006).

Program Evaluation Design

To prepare an evaluation of the proposed time-management intervention, a logic model was created (see Figure 25) to clarify input variables, hypothesized mechanisms of change, expected outcomes, and contextual factors. Based on the expected outcomes described in the logic model, the analyses of the study findings focus on answering the following questions:

1. Were grades improved by the intervention?
    a. It was hypothesized that the group receiving the time-management intervention workshop would have a higher course grade at the end of the semester.
2. Did the process and outcome measures change from pre to post between groups?
    a. It was hypothesized that there would be significant changes in process (TM and SPUSS) and outcome measures (SACQ-A, PSS, CES-D). In terms of process measures, it was hypothesized that both TM and SPUSS would increase significantly in the intervention group as compared to the control group. With regard to the outcome measures, it was hypothesized that there would be a significant increase in SACQ-AA scores and a significant decrease in PSS and CES-D scores in the intervention as compared to the control group.
3. Is the change in outcomes related to process variables controlling for intervention condition?
    a. It is hypothesized that the change in the process variables of SPUSS and TM will predict the change in outcome measures of SACQ-A, PSS, and CES-D, after controlling for the workshop condition and HGPA.

4. Does the intervention workshop change the knowledge of students in the key domains targeted?

a. It is hypothesized that there will be a significant change in self-reported knowledge of students in the domains target by the time-management workshop of those in the intervention condition, and the intervention group will show greater change when compared between groups.

To carry out the analyses involved in Questions 1 and 3, regression models, including hierarchical regression models were used that control of the relevant variables. To examine differences between groups as needed in Question 2, Welch's *t*-test was used to compare difference scores between groups. Given that the study used a randomized design, the use of difference scores is an appropriate statistical method (see Wright 2006, and Rogosa, 1988, for a detailed discussion of methods for between-group comparisons). Finally, to address the change in knowledge which involves ordinal variables in a repeated measures context, paired-sample *t*-test was used for within-group comparison of change over time, and Welch's *t*-test was used for between-group comparison of change.

RESEARCH GOALS

1. Evaluate the effectiveness of a brief self-regulation intervention workshop in teaching students key concepts important to successful time-management, including ego-depletion, multi-tasking, time-chunking, stimulus control, decision fatigue, pre-planning time use, and pre-commitment strategies.
2. Evaluate the effectiveness of this intervention workshop in improving students' perceived time-management skills and socio-emotional outcomes.
3. Examine the impact of intervention on subjective and objective academic outcomes.
4. Share experiences with other researchers, and community stakeholders.

ASSUMPTIONS

- Early intervention can foster self-regulatory skills in undergraduate students, which will have a positive effect on their academic success and university experience.
- Students will engage and learn from the intervention workshop key skills necessary for better time-management.
- When learned, these skills will be put to use by the students.

SITUATION/CONTEXT

1. Transition to first year a difficult time for most students, with a significant number of students not successfully adapting to the post-secondary academic or social demands.
2. Research and feedback from professors of first year courses highlights time-management (and more broadly self-regulatory) skills as a key deficit.
3. York University, as part of a first year retention initiative, is carrying out research and various projects aimed at curbing the attrition rate and increasing student satisfaction.

INPUTS

1. Financial Support for design and implementation of the brief intervention across a number of first year courses.
2. TA/RA who will conduct the workshop outside of class hours, and follow-up information gathering.
3. Faculty willing to allocate bonus grades as incentive for completion of intervention exercises.
4. Random assignment of students to intervention and control group conditions.

INTERVENTION

1. Intervention design including in classroom presentation slides for consistent delivery.
2. 50-minute workshop involving psychoeducation and strategies taught to avoid multitasking, pre-commitment strategies to block distractions, and pre-planning studying time, and provide tools students can use for stimulus control and chunking their study time.
3. Students receive credit for participation in the workshop once having provided evidence that they have tried some of the tools that were presented.

MODERATORS

Proximal Factors:

- The students existing studying and time-management skills.
- External demands on the student's time, including financial pressures and family obligation.
- Student's level of academic motivation

Distal Factors:

- Student familiarity with post-secondary education, including parents who have attended university.
- Past academic performance.

MEDIATORS

- The level of support and structure the student is receiving from the university.
- How much information the student has learned and retained from the workshop
- The degree to which the student has implemented the tools and tactics taught in the workshop.

OUTCOMES

Short Term (End of course)

- Improved academic grades compared to controls.
- Improved sense of time-management skills.
- Improved sense of academic adaptation.
- Improved academic performance based on engagement and use of time-management tools.
- Less stress and low mood as compared to controls

Medium Term (next year)

- Students have retained time-management skills learned during the intervention and continue to use the tools they were introduced to.
- More engagement in extra-curricular activities in the university.

Long Term (up to graduation)

- Increase degree completion
- Increase satisfaction with undergraduate university experience.

PROGRAM EVALUATION (PRE):

1. Gather information on existing student characteristics and achievement history, including high-school GPA.
2. Measure time-management ability, emotional well-being, and perceived academic adaptation.
3. Measure perception of environmental support and structure
4. Test student knowledge of key concepts covered during the intervention.

PROGRAM EVALUATION (POST):

1. Measure and compare with pre-scores time-management score, stress, and perceived academic adaptation. Compare with control group.

FIDELITY & DOSAGE

>Inquire regarding usage of tools and skills covered in the intervention
>Compare student knowledge of key concepts covered during the intervention.

Figure 25

Time-Management Intervention Logic Model

Study Two: Method

Participants and Procedures

The participants comprised students taking the Introductory Psychology course, which was only open to first-year students entering the university, during the winter term of 2017. In this introductory psychology course, students participate in research studies to earn six participation credits required to obtain 4% of their final grade. Students sign up for studies and earn the credits through the Undergraduate Research Participant Pool (URPP) portal. Students are also provided with an alternative option of writing a short essay if they choose to opt out of participating in research studies.

The workshop, titled “Academic Skills and University Challenges Workshop and Discussion Group” was listed on the URPP as one of the studies available for students to participate. Students earned three credits (2% of their final grade) for participating in all three components of the study, which included a pre-workshop questionnaire and the workshop itself, and an end of term questionnaire. With the instructor’s permission, the opportunity to participate in the workshop was advertised through an email sent in January to the incoming first-year class containing 127 students (Please see Appendix B: Study Protocols for details including the full text of communications). In total, 59 students completed the pre-workshop questionnaire and signed up for one of the workshops. Both the control and intervention workshop were offered twice to accommodate more students attending. Four workshops were held during the evening from 5:30 pm to 6: 45 pm starting on Monday, January 30th, 2017, to Thursday, February 2nd, 2017, of which the students were only allowed to attend one. The workshops were held in a room close to where the students would have their lecture later in the evening. Two of the four evenings the workshop consisted of the intervention condition and was attended by 34 students.

During the other two evenings, an active placebo control group was conducted in the form of a facilitated discussion regarding challenges commonly faced by first-year students, attended by 25 students. The students were not aware of the existence of two separate conditions which formed the basis of randomization.

The intervention workshop involved a didactic and interactive presentation on the topics reviewed in the previous section, such as multi-tasking, ego-depletion, precommitment strategies and other topics (see slide show located in Appendix B). The students were given a handout which they could use to take notes during the presentation. They were also provided with a time table depicting the hours in a week to create a study plan as part of the study time preplanning activity discussed in the workshop. Upon completion of the intervention workshop, the participants were asked to e-mail the researcher a screenshot of their computer showing that they have installed one of the precommitment digital tools discussed in the workshop, as well as a picture of a weekly calendar showing their pre-planned study schedule.

The placebo control workshop involved a facilitated discussion group, whereby the presenter did not provide any didactic information. Instead, questions were posed, and participants took turns answering or reflecting on another respondent's answer. A list of questions used to standardize this session is provided in Appendix B. Questions were on the topic of transitioning to university, such as "What are some of the challenges you've faced since you started university?" or "What are some lessons you've learned that have helped you adapt to university life?"

Following the workshops, during the month of March, participants were emailed a link to an online survey and earned one credit for completing it. Of the 59 students who attended the workshop, 55 completed the final questionnaires. The four students who did not complete the final questionnaire also did not have any final grades for the course, indicating that they had likely withdrawn from the course.

Participants were 58% female and 42% male students, with an average self-reported high school graduating GPA of 79.7%. Incoming students were also asked about their relative financial situation, and 25.4% reported to be below average, 54.2% reported to be average, 11.9% reported to be above average, and 8.5% reported themselves to be well above average in terms of their socio-economic status.

Measures

Demographic variables. Demographic information was collected in the pre-workshop survey. Variables included participant's age, gender, high school grade point average, current academic year, and perceived socioeconomic status.

Intervention Concepts Rating. Students were asked to rank how familiar they were with several key concepts covered in the intervention, including: "Ego Depletion, Decision Fatigue, Effects of Multi-Tasking on attention, Precommitment Strategies, and the Pomodoro Technique."

The Center for Epidemiological Study of Depression Scale (CES-D; Radloff, 1977). Please see Study One for a detailed description. The reliability of the scale in the present sample ranged from $\alpha = 0.87$ pre-workshop to $\alpha = 0.89$ post-workshop.

Perceived Stress Scale (PSS; Cohen, 1986). Please see Study One for a detailed description. The reliability of the scale in the present sample ranged from $\alpha = 0.86$ pre-workshop to $\alpha = 0.92$ post-workshop.

Time-management (TM; Rog & Pancer, unpubl.). Please see Study One for a detailed description. The reliability of the scale in the present sample ranged from α = 0.91 pre-workshop to α = 0.92 post-workshop.

Student Adaptation to College Questionnaire (SACQ; Baker & Siryk, 1984). Please see Study One for a detailed description. The reliability of the scale in the present sample ranged from α = 0.87 pre-workshop to α = 0.88 post-workshop.

Students' Perception of University Support and Structure (SPUSS; Wintre, Gates, Pancer, Pratt, Polivy, Birnie-Lefcovitch, & Adams, 2009). Please see Study One for a detailed description. The reliability of the scale in the present sample ranged from α = 0.85 pre-workshop to α = 0.87 post-workshop.

The number of observations, mean, standard deviation, and descriptive statistics for the three outcome measures (SACQ, PSS, CES-D) and two process measures (TM, SPUSS) obtained pre-workshop are presented in Table 14.

Table 14
Descriptive Statistics of Demographic and Scale Measures Prior to Attending the Workshops

Statistic	N	Mean	St. Dev.	Min	Median	Max
Age	59	19.61	1.72	18	19	25
Self-Reported Income	59	2.03	0.85	1	2	4
Self-Reported High School GPA	59	79.73	8.17	60	80	98
TM (Mean)	59	2.53	0.59	1.36	2.55	3.91
SPUSS (Mean)	59	6.10	0.96	3.95	6.00	8.10
SACQ-AA (Mean)	59	5.74	1.11	3.25	5.75	7.88
PSS (Mean)	59	1.71	0.55	0.71	1.64	3.00
CES-D (Mean)	59	0.85	0.47	0.10	0.75	2.10

Study Two: Results

The results section comprises analyses to describe differences before and after the intervention between the two experimental and control groups. First, demographic and descriptive statistics are provided for the samples. Subsequently, the hypotheses posed in the previous section are addressed, including examining the impact of the intervention on grades, process, and outcome measures, as well as the relationship between the change in process variables and outcome measures. Finally, students' change in knowledge and satisfaction with both conditions is examined. An alpha level of .05 was chosen prior to the study for all questions posed in this section.

The statistical software R, version 3.4.4, alongside R Studio, Version 1.1.442, was used for following analyses. For a complete list of R packages used, please see Appendix B. Furthermore, to enhance statistical verification and research reproducibility, the code that was used to produce the statistical results and graphics using R Statistical Software is made available in an addendum (Appendix C – CODE).

Description of Sample

In total 59 participants signed up for and attended one of the intervention or control workshops. Of these 59 participants, four did not complete the study, resulting in a 6.7% attrition rate. (3 in the intervention and 1 in the control condition). There were 24 participants in the control workshop condition and 31 participants in the time-management intervention workshop. Descriptive statistics for the demographic information, three outcome measures (SACQ, PSS, CES-D), and two process measures (TM, SPUSS) are presented in Table 15 and Table 16, for the control and intervention groups respectively. The correlation between the variables in the study prior to the workshop are presented in Table 17. The correlations between the variables prior to the workshop and at the end of term are presented in Table 18 and Table 19, for the control and intervention groups respectively.

To screen for random or careless responders, the inter-item standard deviation (ISD) was used (Marjanovic et al., 2015), and their distributions are included in Appendix B. No cases of concern with regards to random responding were noted.

Comparing the attributes of the two workshop groups did not reveal any significant difference between their demographic attributes, including gender proportions $\chi^2(1) = 0.002$, $p = .96$, self-reported income levels $\chi^2(3) = 1.33$, $p = .72$, self-reported high school graduating GPA $t(56.93) = 0.86$, $p = .39$.

Table 15
Control Group: Descriptive Statistics of Demographic and Scale Measures post Workshop

Statistic	N	Mean	St. Dev.	Min	Median	Max
Age	24	19.12	1.19	18	19	22
Self-Reported Income	24	2.00	0.93	1	2	4
Self-Reported High School GPA	24	80.42	6.78	70	80	96
TM Post Scores (Mean)	24	2.17	0.65	0.64	2.41	3.00
SPUSS Post Scores (Mean)	24	6.31	1.02	4.25	6.40	7.90
SACQ-AA Post Scores (Mean)	24	5.03	1.06	2.96	5.06	6.75
PSS Post Scores (Mean)	24	2.33	0.63	1.14	2.32	3.64
CES-D Post Scores (Mean)	24	1.23	0.53	0.25	1.23	2.05

Table 16
Intervention Group: Descriptive Statistics of Demographic and Scale Measures post Workshop

Statistic	N	Mean	St. Dev.	Min	Median	Max
Age	31	20.03	1.97	18	19	25
Self-Reported Income	31	2.03	0.80	1	2	4
Self-Reported High School GPA	31	78.81	9.38	60	75	98
TM Post Scores (Mean)	31	2.75	0.54	1.55	2.73	3.82
SPUSS Post Scores (Mean)	31	6.39	1.05	4.20	6.30	8.60
SACQ-AA Post Scores (Mean)	31	6.08	1.01	4.42	5.75	8.29
PSS Post Scores (Mean)	31	1.64	0.72	0.29	1.64	3.29
CES-D Post Scores (Mean)	31	1.12	0.50	0.45	1.05	2.55

Table 17

Correlation Table of Process and Outcome Variables Prior to Workshop

Variable	1	2	3	4	5	6	7
1. Age							
2. SES	-.12 [-.37, .14]						
3. High Sch. GPA	-.03 [-.28, .23]	.25 [-.01, .48]					
4. TM	.14 [-.12, .39]	.04 [-.22, .30]	.44** [.20, .62]				
5. SPUSS	.14 [-.12, .38]	-.09 [-.34, .17]	-.09 [-.34, .17]	.28* [.03, .50]			
6. SACQ-AA	.37** [.12, .57]	.10 [-.16, .34]	.24 [-.01, .47]	.55** [.35, .71]	.43** [.20, .62]		
7. PSS	-.20 [-.44, .06]	.20 [-.06, .43]	.21 [-.05, .44]	-.18 [-.42, .08]	-.43** [-.62, -.20]	-.40** [-.59, -.16]	
8. CES-D	-.12 [-.36, .15]	.03 [-.23, .29]	.12 [-.14, .37]	-.01 [-.27, .24]	-.29* [-.51, -.04]	-.34** [-.55, -.09]	.66** [.49, .79]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Table 18

Correlation Table of Process and Outcome Variables Pre and Post Workshop for the Control Group

Variable	1	2	3	4	5	6	7	8	9	10
1. High Sch. GPA										
2. TM Pre	.35 [-.06, .66]									
3. SPUSS Pre	.16 [-.26, .53]	.44* [.05, .72]								
4. SACQ-AA Pre	.37 [-.04, .67]	.68** [.39, .85]	.42* [.02, .71]							
5. PSS Pre	.30 [-.12, .63]	-.19 [-.55, .23]	-.33 [-.65, .08]	-.40 [-.69, .01]						
6. CES-D Pre	.20 [-.22, .56]	-.17 [-.54, .25]	-.23 [-.58, .19]	-.33 [-.65, .08]	.70** [.41, .86]					
7. TM Post	.15 [-.27, .52]	.48* [.09, .74]	-.27 [-.61, .15]	.25 [-.17, .60]	.12 [-.30, .50]	.14 [-.28, .52]				
8. SPUSS Post	.18 [-.24, .54]	.50* [.12, .75]	.44* [.04, .71]	.71** [.42, .86]	-.57** [-.79, -.22]	-.40 [-.69, .00]	-.05 [-.44, .36]			
9. SACQ-AA Post	.31 [-.11, .63]	.58** [.23, .80]	.11 [-.31, .49]	.69** [.39, .85]	-.18 [-.55, .24]	-.06 [-.45, .35]	.43* [.03, .71]	.32 [-.09, .64]		
10. PSS Post	.06 [-.35, .46]	-.42* [-.71, -.03]	-.04 [-.43, .37]	-.66** [-.84, -.36]	.50* [.12, .75]	.48* [.10, .74]	-.36 [-.67, .05]	-.51* [-.76, -.14]	-.68** [-.85, -.38]	
11. CES-D Post	-.09 [-.48, .33]	-.32 [-.64, .10]	-.16 [-.53, .26]	-.50* [-.75, -.13]	.36 [-.05, .67]	.51* [.13, .76]	-.23 [-.58, .19]	-.44* [-.72, -.05]	-.50* [-.75, -.13]	.68** [.38, .85]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Table 19

Correlation Table of Process and Outcome Variables Pre and Post Workshop for the Intervention Group

Variable	1	2	3	4	5	6	7	8	9	10
1. High Sch. GPA										
2. TM Pre	.49** [.17, .72]									
3. SPUSS Pre	-.17 [-.50, .19]	.18 [-.18, .51]								
4. SACQ-AA Pre	.15 [-.22, .48]	.42* [.07, .67]	.51** [.19, .73]							
5. PSS Pre	.24 [-.13, .55]	-.04 [-.39, .32]	-.56** [-.77, -.26]	-.33 [-.61, .03]						
6. CES-D Pre	.11 [-.25, .45]	.16 [-.20, .49]	-.38* [-.64, -.02]	-.32 [-.61, .03]	.64** [.37, .81]					
7. TM Post	.53** [.22, .75]	.43* [.09, .68]	-.15 [-.48, .22]	.25 [-.12, .55]	.26 [-.11, .56]	-.09 [-.43, .27]				
8. SPUSS Post	-.01 [-.37, .34]	.04 [-.31, .39]	.61** [.32, .79]	.33 [-.03, .61]	-.39* [-.65, -.04]	-.24 [-.55, .13]	-.08 [-.42, .28]			
9. SACQ-AA Post	.23 [-.13, .54]	.33 [-.03, .61]	.48** [.16, .72]	.62** [.34, .80]	-.29 [-.58, .07]	-.42* [-.67, -.07]	.47** [.14, .71]	.44* [.10, .69]		
10. PSS Post	-.15 [-.48, .22]	-.15 [-.48, .21]	-.38* [-.65, -.03]	-.33 [-.61, .03]	.18 [-.18, .50]	.46** [.12, .70]	-.48** [-.71, -.15]	-.36* [-.63, -.01]	-.79** [-.89, -.60]	
11. CES-D Post	-.04 [-.39, .32]	.05 [-.31, .40]	-.20 [-.52, .16]	.03 [-.33, .38]	.40* [.05, .66]	.68** [.43, .83]	-.19 [-.51, .17]	.00 [-.35, .36]	-.37* [-.64, -.02]	.53** [.22, .75]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Changes in Process and Outcome Measures Post Workshop

To examine the change in scores before and after attending the workshop between the control and intervention groups, Welch's *t*-tests were conducted on the difference scores obtained from subtracting pre and post scores of each group.

There was a significant difference in the change in students' Academic Adjustment scores (SACQ-AA) after attending the workshop intervention compared to the control groups $t(51.24) = 3.76$, $p < .001$. The Academic Adjustment scores of the students in the intervention group had increased after the workshop in comparison to the control group, with a large effect size, $d = 1.02$. Figure 26 depicts the distribution and mean of both groups before and after attending the workshop.

The change in students' PSS scores after attending the workshop was significantly different between the intervention and control groups $t(52.78) = -2.91$, $p = .005$. The PSS scores of the students in the intervention group had decreased relative to that of the control group, with a medium effect size, $d = -0.79$. Figure 27 depicts the distribution and mean of both groups before and after attending the workshop.

The change in students' CES-D scores after attending the workshop was not significantly different between the intervention and control groups $t(44.03) = -1.34$, $p = .19$. Figure 28 depicts the distribution and mean of both groups before and after attending the workshop.

The change in students' TM scores after attending the workshop was significantly different between the intervention and control groups $t(49.78) = 2.7$, $p = .009$. The TM scores of the students in the intervention group had increased after the workshop to relative to that of the control group, with a medium effect size, $d = .73$. Figure 29 depicts the distribution and mean of both groups before and after attending the workshop.

The change in students' SPUSS scores after attending the workshop was not significantly different between the intervention and control groups, $t(45.51) = 0.52$, $p = .60$. Figure 30 depicts the distribution and mean of both groups before and after attending the workshop.

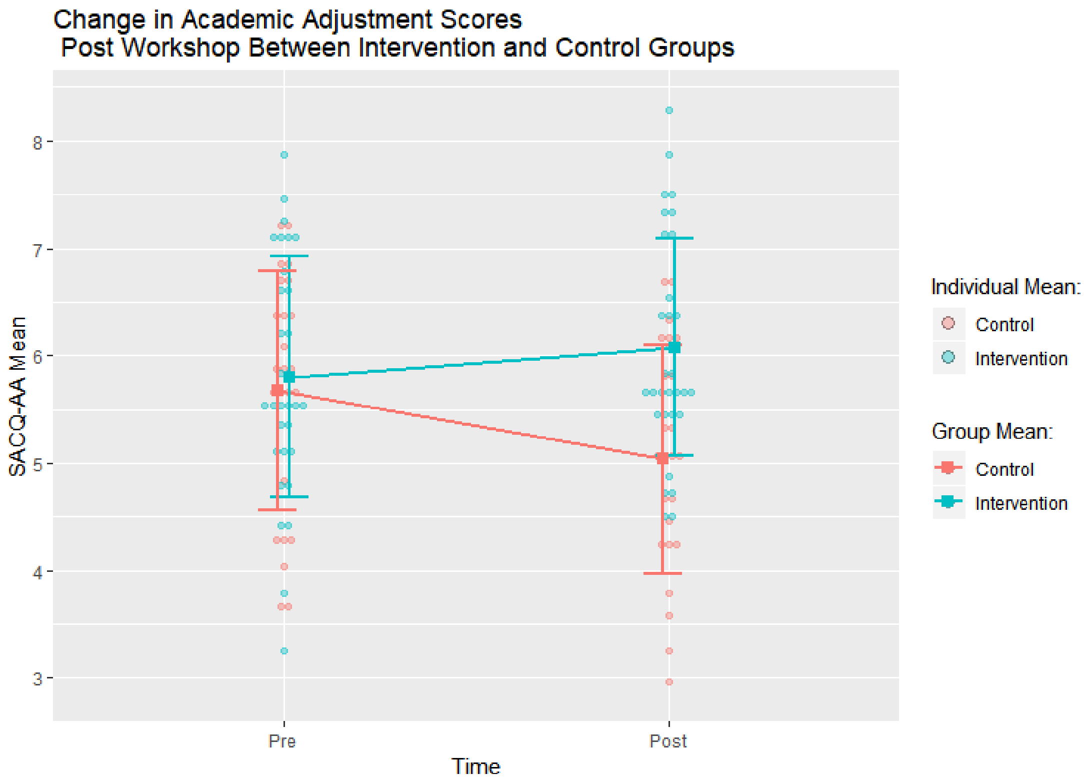

Figure 26
Change in Academic Adjustment Scores before and after Workshop Attendance.

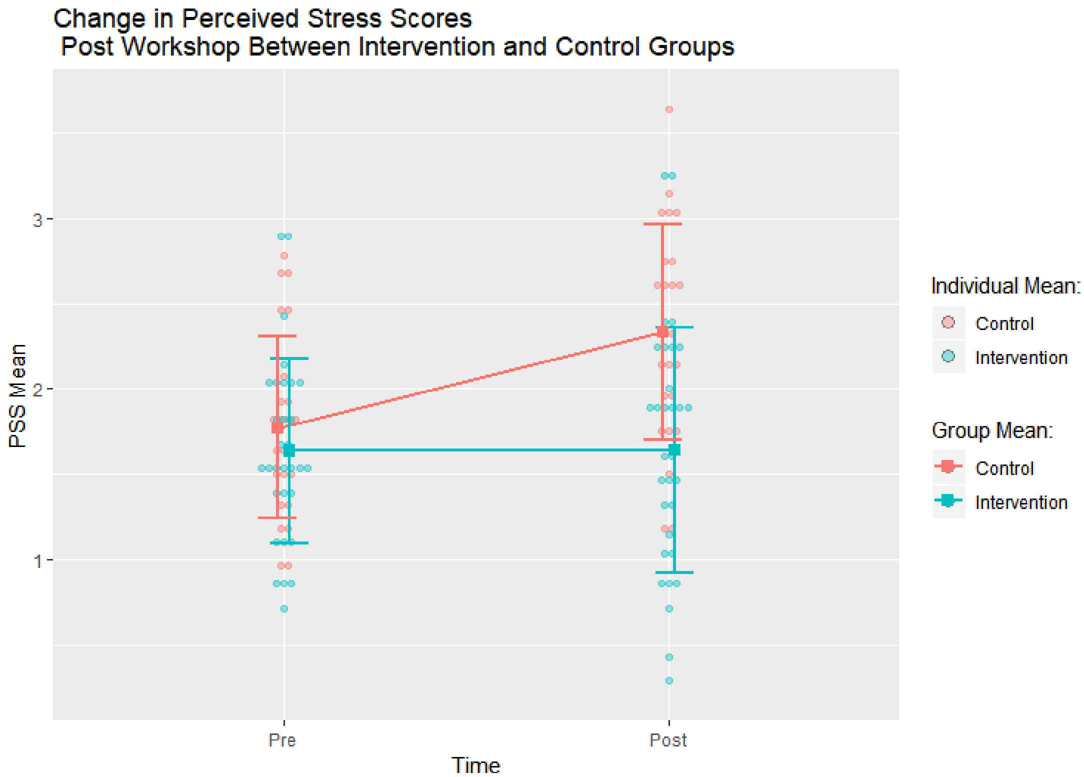

Figure 27
Change in Perceived Stress Scores before and after Workshop Attendance.

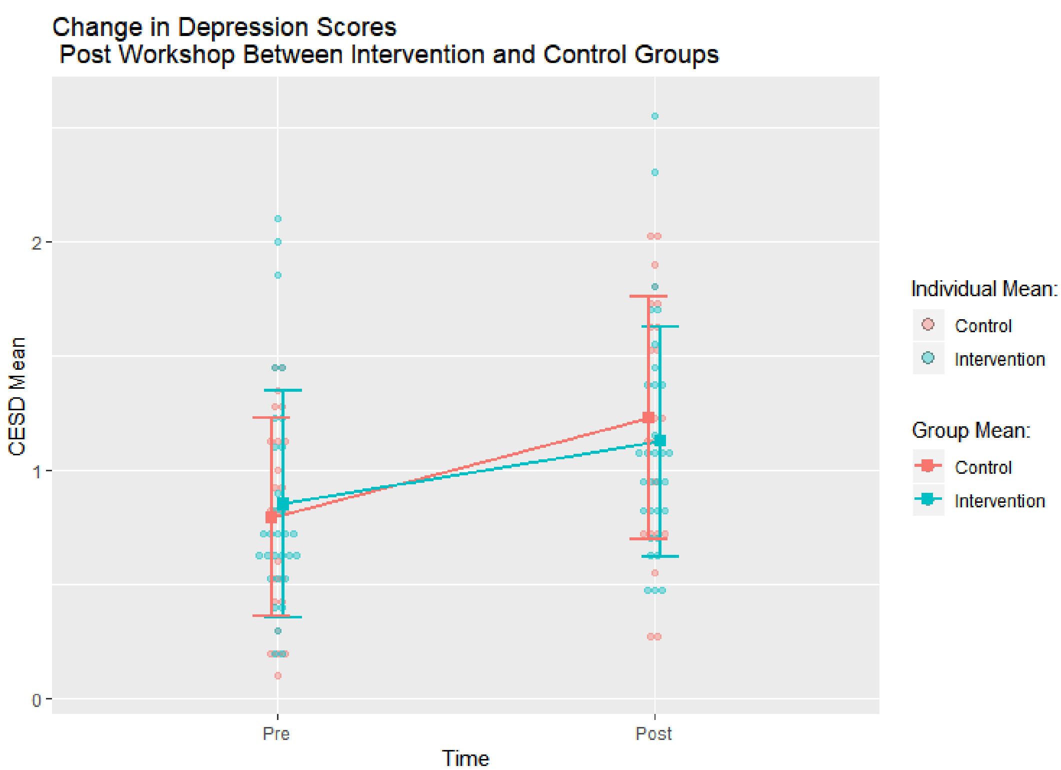

Figure 28
Change in Depression Scores before and after Workshop Attendance.

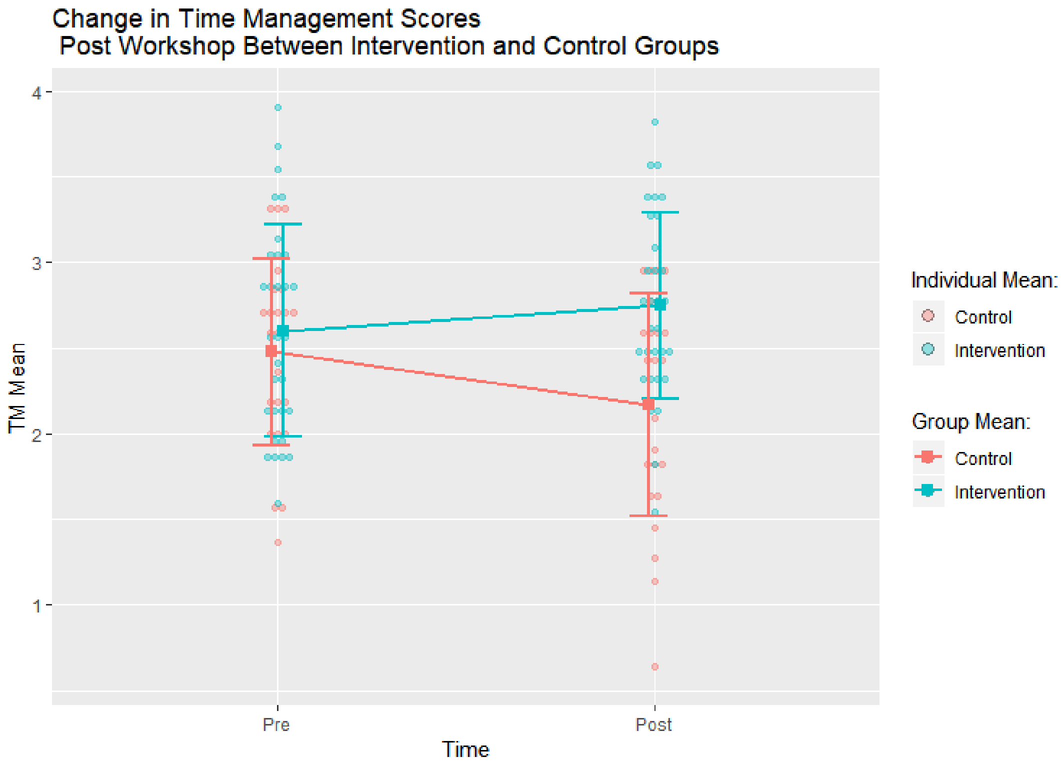

Figure 29
Change in Time-management Scores before and after Workshop Attendance.

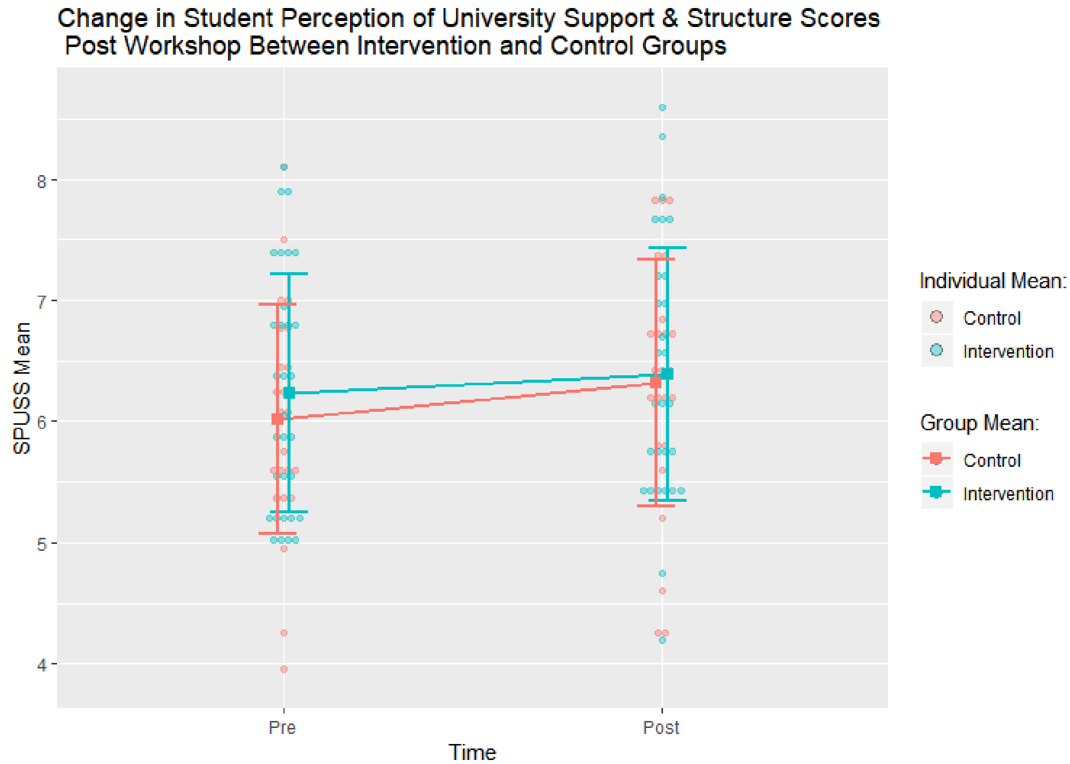

Figure 30
Change in Student Perception of University Support and Structure before and after Workshop Attendance

Change in Outcome Variables as Predicted by Change in Process Variables

In the previous section, it was revealed that the changes in the outcome measures of Academic Adjustment and PSS from prior to post workshop were significantly different between the intervention and control group. The present section examines whether the changes in scores are related to changes in the process variables (TM and SPUSS). Both workshop groups were combined, and while controlling for workshop condition, the change scores in the process variables were regressed on the change scores of the outcome measures which incurred significant differences in the previous section (e.g., SACQ-AA and PSS).

The regression results with the change scores in Academic Adjustment as the criterion are presented in Table 20. As the table indicates, the regression model was significant and accounted for about 26% of the variance in the changes in SACQ. In particular, the change scores TM were significant and made a unique contribution to the model beyond what could be explained by workshop condition. Change scores in SPUSS were not a significant predictor.

The regression results with the change scores in PSS as the criterion are presented in Table 21. As the table indicates, the regression model was significant and accounted for about 26% of the variance in the changes in PSS. The change scores in TM were the only significant predictor of the changes in PSS from before to after the workshop.

Table 20
Regression Results with Change in SACQ as the Criterion

Predictor	*b*	*S.E.*	sr^2	Fit
(Intercept)	-0.48*	0.19		
Change in SPUSS	-0.01	0.12	.00	
Changes in TM	0.50*	0.19	.09	
Workshop	0.69**	0.25	.10	
				R^2 = .300
				Adj. R^2 = .26
				*F (df = 3;51) = 7.29***

Note. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. * indicates p < .05. ** indicates p < .01.

Table 21
Regression Results with Change in PSS as the Criterion

Predictor	*b*	S.E.	sr^2	Fit
(Intercept)	0.46**	0.15		
Change in SPUSS	-0.08	0.1	.01	
Changes in TM	-0.39*	0.15	.10	
Workshop	-0.38	0.20	.05	
				R^2 = .249
				Adj. R^2 = .20
				*F (df = 3;51) = 5.64***

Note. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. * indicates p < .05. ** indicates p < .01.

Impact of the Intervention on Course Grades

A hierarchical regression was used to examine whether the students' final course grades in the Psych 1010 course were impacted by attending the workshop. Controlling for pre-existing factors such as high school graduating GPA and SES, workshop condition (with the control workshop coded as 0 and intervention workshop coded as 1) was used to predict students' final course grade. Subsequently, the interaction of high school graduating GPA with workshop condition was also examined. Results are presented in Table 22.

The first regression block contained SES and high school GPA, and it was a significant predictor of course grades, accounting for about 13% of the variance (See Table 22 for details). Only high school GPA was a significant predictor. The second block added workshop as a predictor, which resulted in a significant improvement to the model fit, with the combination of predictors accounting for 23% of the variance. Being part of the intervention group was predictive of higher grades, and it accounted for approximately 10% of the variation in the final course grades controlling for SES and high school GPA. The third block added the interaction of high school GPA and workshop condition, which although in the direction hypothesized (i.e., students with lower high school GPA benefiting more from the intervention) was not a significant predictor.

Table 22

Hierarchical Regression Results with Final Course Grades as the Criterion

Block/Predictor	*b*	*S.E.*	sr^2	Fit	Difference	*p*
Block 1 (Demographics)						
(Intercept)	34.50	13.91				.016
SES	2.69	1.75	.04			.131
High School GPA	0.42	0.179	.09			.023
				F = 5.03		.010
				R^2 = .16		
				Adj. R^2 = .13		
Block 2 (Intervention)						
(Intercept)	26.79	13.41				.051
SES	2.49	1.65	.03			.137
High School GPA	0.47	0.17	.11			.008
Intervention	7.52	2.74	.11			.008
				F = 6.29		.001
					ΔF = 1.26	.008
				R^2 = .27		
				Adj. R^2 = .23	Δ *Adj.* R^2 = .097	
Block 3 (Interaction between Intervention and High School GPA)						
(Intercept)	-11.04	24.36				.652
SES	2.20	1.62	.03			.182
High School GPA	0.95	0.31	.13			.003
Intervention	60.28	28.76	.06			.041
H.S. GPA X Intervention	-0.66	0.36	.05			.071
				F = 5.79		<.001
					ΔF = *negative*	N/A
				R^2 = .32		
				Adj. R^2 = .26	Δ *Adj.* R^2 = .034	

Note. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared.

Change in Knowledge

Students were asked about their knowledge of key concepts covered in the intervention workshop condition before attending and at the post data collection. To examine the potential change in knowledge in each group, both workshop groups responses were compared from pre to post separately. Related sample's *t*-test was used to assess intragroup change. The second question of interest was the difference in the magnitude of change between groups. Intergroup differences in terms of change scores were assessed using Welch's *t*-test on the difference scores.

Students were asked about their knowledge regarding the impact of multitasking on attention and learning. Students' self-reported knowledge in this domain increased significantly both in the intervention group, $t(30) = 9.63$, $p < .001$, and the control group, $t(23) = 4.01$, $p < .001$. Comparing the magnitude of change between groups revealed a significant difference, $t(50.92) = 3.61$, $p < .001$. Students' self-reported knowledge regarding multitasking's impact on learning and attention had increased significantly more in the intervention group as compared to the change in knowledge reported by the control group. The distribution of responses in both workshop groups prior and after the workshop is illustrated in Figure 31.

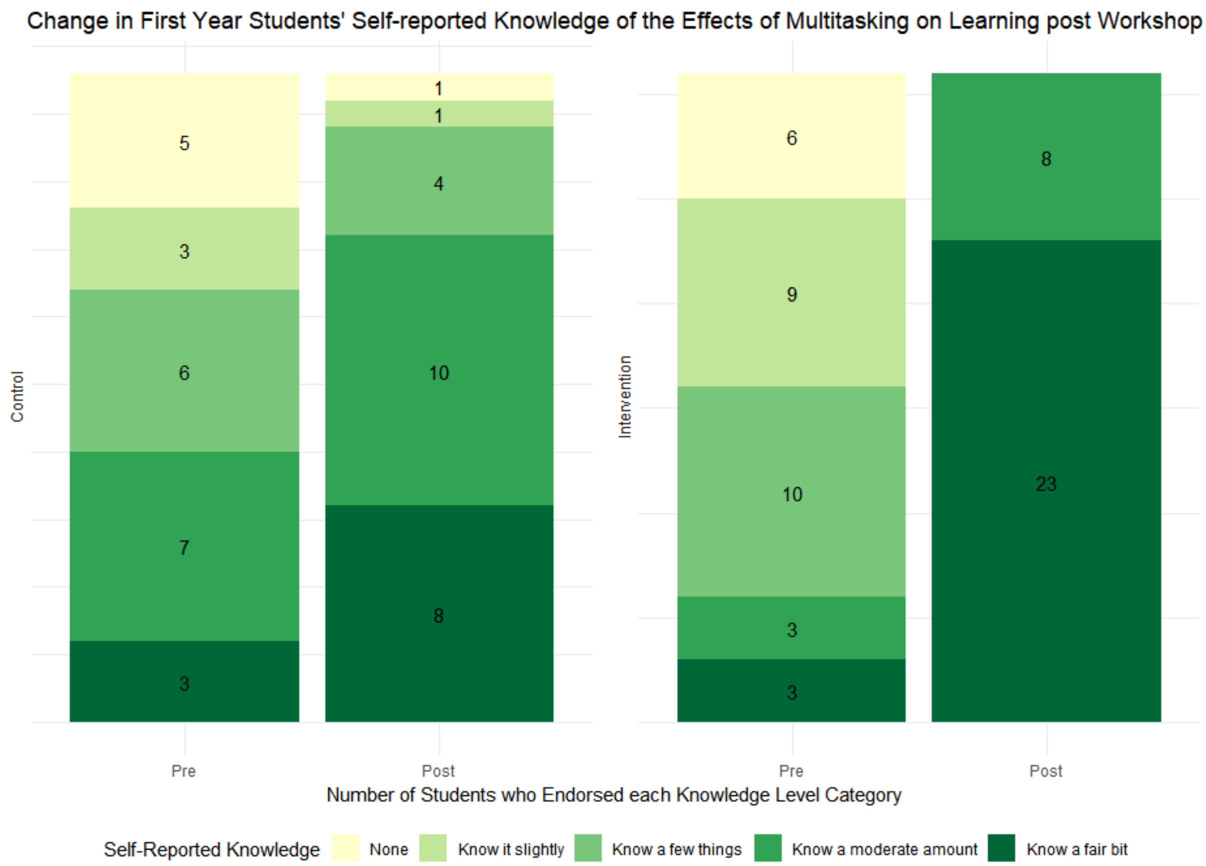

Figure 31
Change in self-reported knowledge regarding multitasking's impact on attention and learning.

Students were asked about their knowledge of precommitment strategies. Students' self-reported knowledge in this domain increased significantly in the intervention group, $t(30) = 9.87$, $p < .001$, but not in the control group, $t(23) = 1.00$, $p = .328$. Comparing the magnitude of change between groups revealed a significant difference, $t(48.45) = 7.83$, $p < .001$. Students' self-reported knowledge regarding precommitment strategies had increased significantly more in the intervention group as compared to the change in knowledge reported by the control group. The distribution of responses in both workshop groups prior and after the workshop is illustrated in Figure 32.

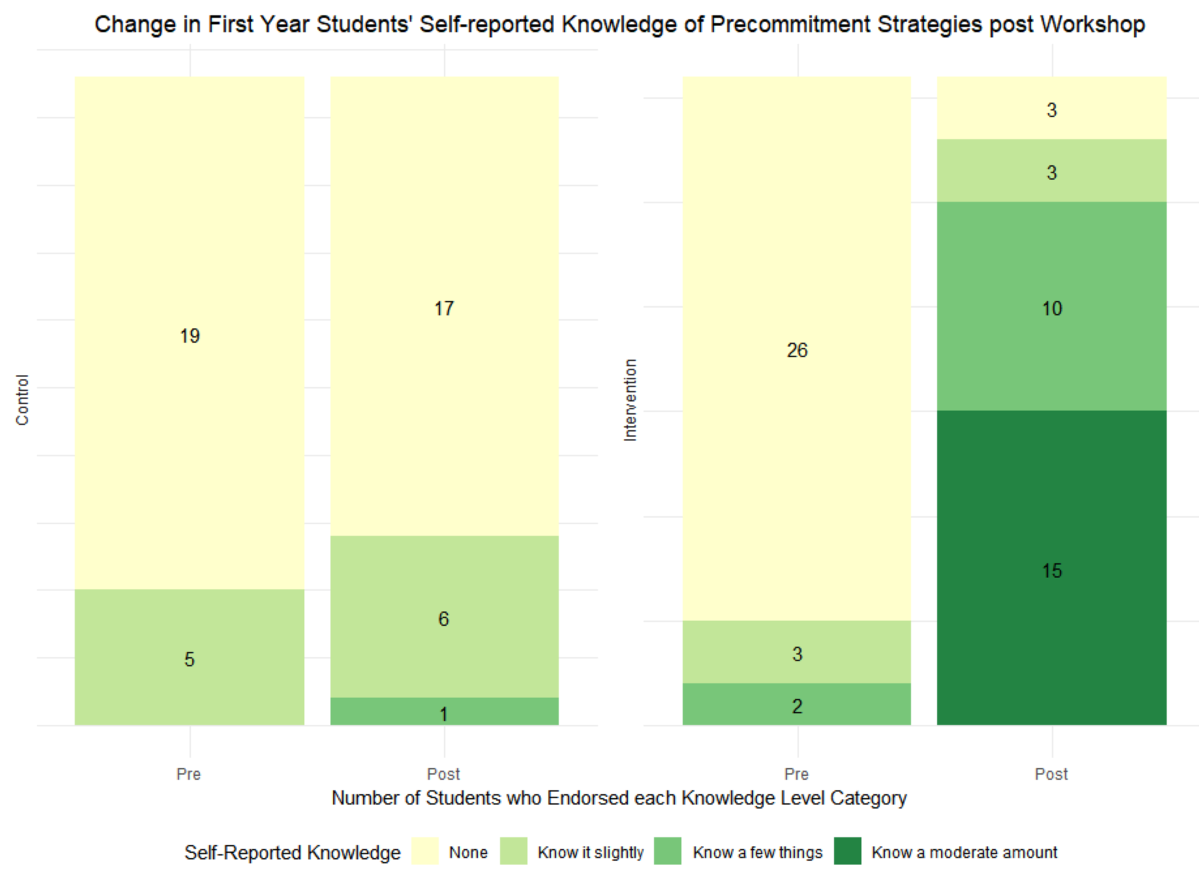

Figure 32
Change in self-reported knowledge regarding precommitment strategies.

Students were asked about their knowledge regarding the concept of decision fatigue. Students' self-reported knowledge in this domain increased significantly in the intervention group, $t(30) = 15.24$, $p < .001$, but not in the control group, $t(23) = 1.42$, $p = .170$. Comparing the magnitude of change between groups revealed a significant difference, $t(52.98) = 10.64$, $p < .001$. Students' self-reported knowledge regarding decision fatigue had increased significantly more in the intervention group as compared to the change in knowledge reported by the control group. The distribution of responses in both workshop groups prior and after the workshop is illustrated in Figure 33.

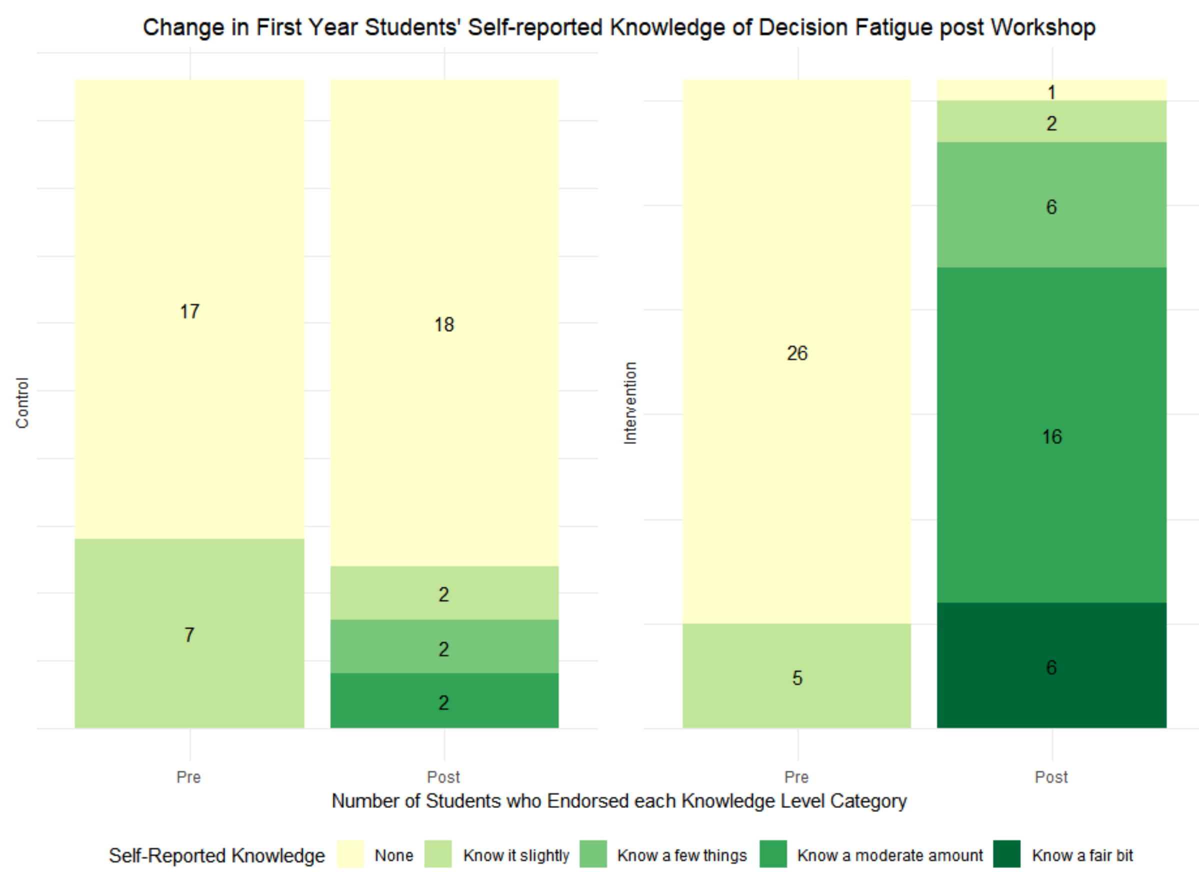

Figure 33
Change in self-reported knowledge regarding decision fatigue.

Students were asked about their knowledge regarding the concept of ego depletion. Students' self-reported knowledge in this domain increased significantly both in the intervention group, $t(30) = 11.57$, $p < .001$, and the control group, $t(23) = 7.01$, $p < .001$. Comparing the magnitude of change between groups did not reveal any significant differences, $t(46.87) = 1.70$, $p = .095$. The distribution of responses in both workshop groups prior and after the workshop is illustrated in Figure 34.

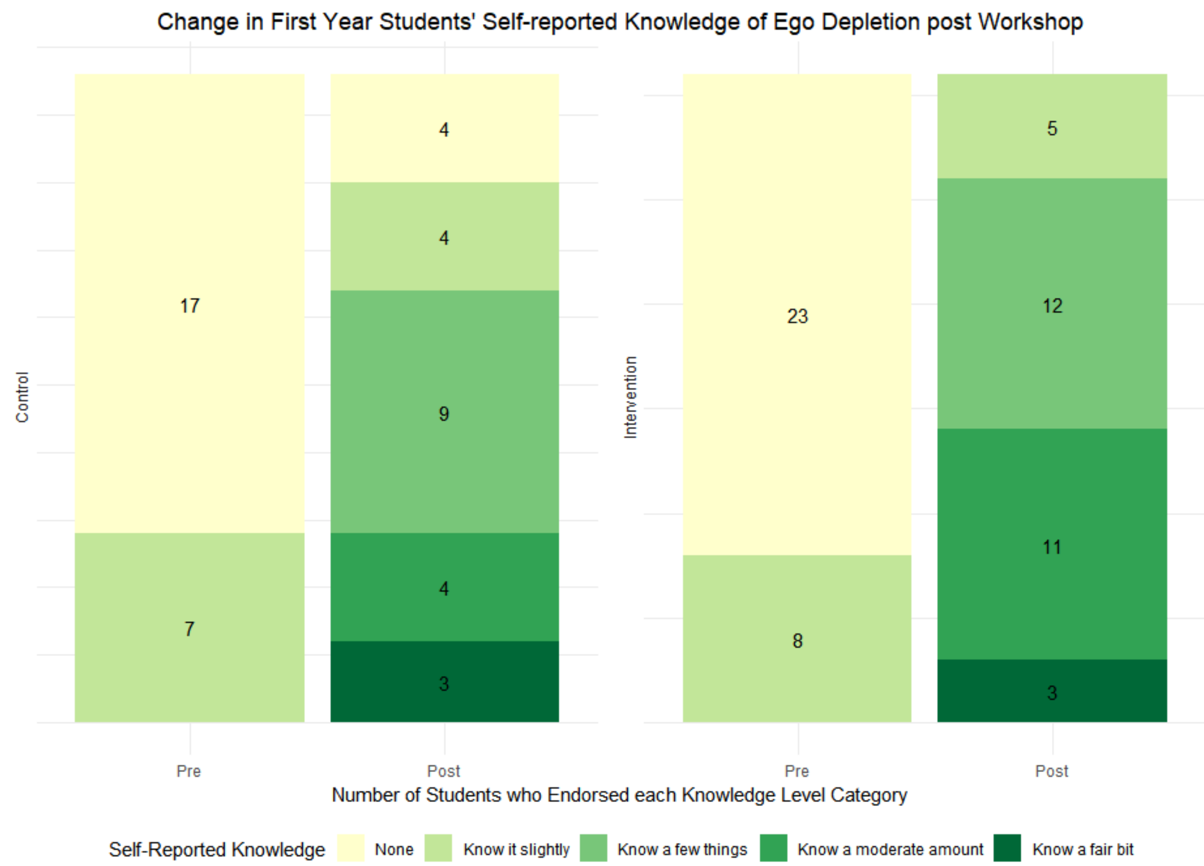

Figure 34
Change in self-reported knowledge regarding ego depletion.

Students were asked about their knowledge regarding the Pomodoro Technique. Students' self-reported knowledge in this domain increased significantly in the intervention group, $t(30) = 12.54$, $p < .001$, but not in the control group, $t(23) = 0.17$, $p = .866$. Comparing the magnitude of change between groups revealed a significant difference, $t(52.21) = 8.79$, $p < .001$. Students' self-reported knowledge regarding the Pomodoro technique had increased significantly more in the intervention group as compared to the change in knowledge reported by the control group. The distribution of responses in both workshop groups prior and after the workshop is illustrated in Figure 35.

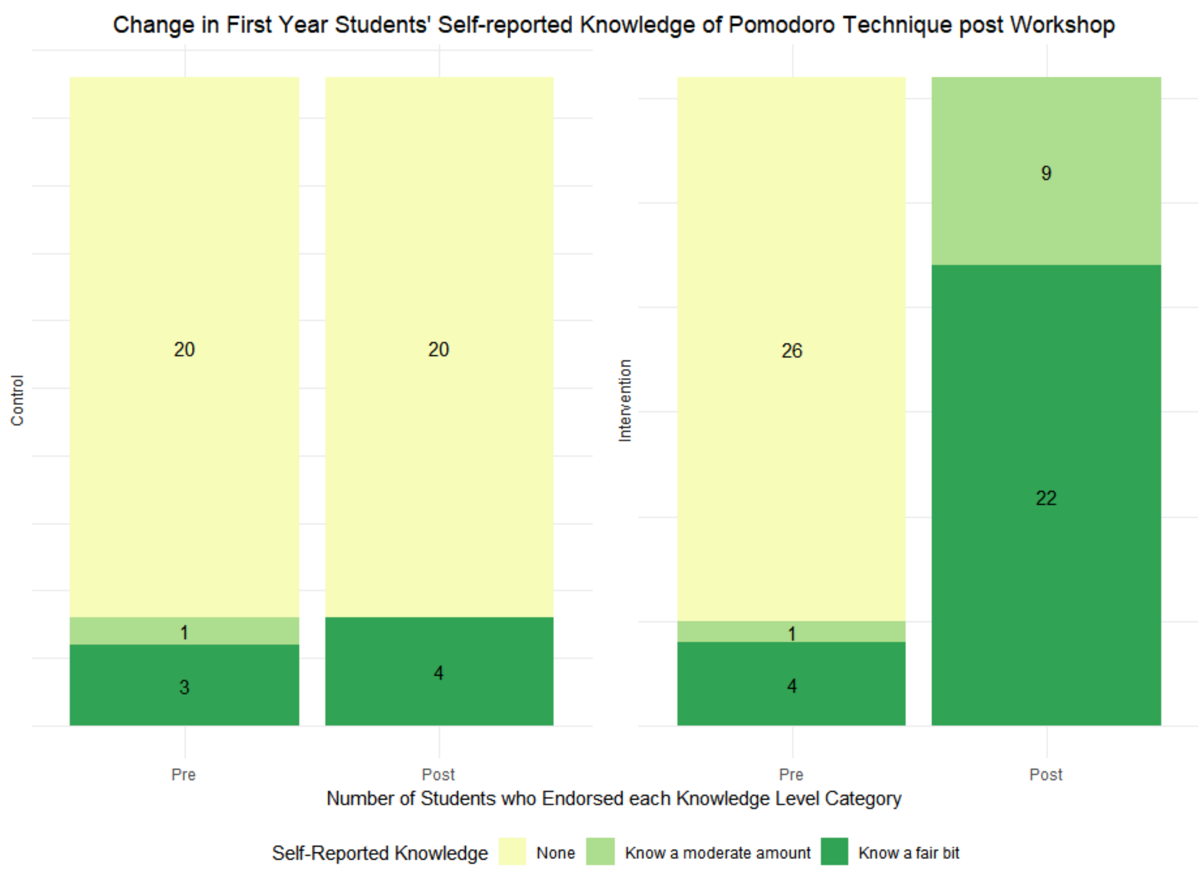

Figure 35
Change in self-reported knowledge regarding the Pomodoro technique.

Study Two: Discussion

The present study aimed to develop and evaluate an effective intervention for supporting the improvement of students' self-regulatory skills. This intervention was built on insights gained from the longitudinal study of the development of self-regulation and external regulation in emerging adults during the transition to university, and their impact on adjustment and psychological well-being. We chose specific elements of the intervention based on the information obtained from the recent literature on challenges faced by students in regulating their behaviour and time-management, with a particular focus on academic behaviours. Participants learned about and practiced skills such as avoiding multitasking, using pre-commitment strategies, pre-planning their studying schedule, and structuring their digital and physical environment to avoid distractions. Overall, students reported enjoying the workshop and benefitting from its content (see Satisfaction Survey results presented in Figure 36).

Intervention in Relation to Course Grades

The design and program evaluation of the intervention was articulated in the logic model presented in Figure 25. Based on the expected outcomes and mechanisms of change described in the logic model, the analysis of the data addressed a number of hypotheses. First, the impact of the intervention on grades was examined. A hierarchical regression was used to examine if the students' final course grade in the Psych 1010 course were impacted by attending the workshop, controlling for pre-existing factors such as high school graduating GPA (HGPA) and SES. In line with the prior hypothesis (1a) being part of the intervention group was predictive of higher grades, and it accounted for approximately 10% of the variation in the final course grades after controlling for SES and high school GPA. It is noteworthy that the impact of the intervention was comparable, in terms of variance explained, to the influence of HGPA, which was entered in the previous block.

Intervention in Relation to Process and Outcome Measures

Next, the process and outcome variables of interest were examined for changes before and following the workshop at the end of the semester, with a focus on discerning any differing degrees of change between the control and intervention group during that time. Of the three outcome measures, two had significant differences between the two groups over time. Compared to the control group, Academic Adjustment scores of the students in the intervention group increased after the workshop with a large effect size; and the perceived stress scores of the students in the intervention group had decreased, with a medium effect size. These differences partially confirmed the hypothesis regarding intervention outcomes (Hypothesis 2a). Interestingly, depression scores did not significantly differ between the intervention and control groups over time. Given the difference in perceived stress scores between the control and intervention groups, it is possible that, with further time, depression ratings would have also diverged, due to the predictive influence of stress on the occurrence of depression in emerging adults (Sheets & Craighead, 2014). However, this is a question for future research to address.

Similar to the outcome measures, there was also a significant change between the groups in the process measure of TM as hypothesized (2a), but not SPUSS. The TM scores of the students in the intervention group had increased after the workshop to a greater extent relative to that of the control group, with a medium effect size. However, the two groups did not differ in the rate of change they experienced in SPUSS. Given both the didactic and practical focus of the workshop, with hands-on training, the increase in the students' perceived self-regulatory abilities was anticipated. With regards to the change in SPUSS, it is likely that both the students in the control and intervention group experienced support in attending the workshops and benefited in diverse ways. This diverse learning was particularly the case of the control group since many students shared their own experience and lessons learned, not only normalizing the difficult transition process but also providing practical recommendations to each other (for a list of questions used to facilitate the control condition of the workshop see Appendix E).

The Mechanisms of Change

Of particular interest to our program evaluation were the mechanisms of change. Specifically, we examined whether the change in outcome variables was related to the change in process across all participants. It was hypothesized (3a) that the change in the process variables of SPUSS and TM would predict the change in the outcome measures that had differed significantly between groups. Using difference scores in both process (TM and SPUSS) and outcome measures (PSS and SACQ-AA) in regression models, it was revealed that TM change scores were significant and made a unique contribution to the model beyond what could be explained by workshop condition. These findings suggest that the key ingredient driving the improved outcomes for students is the increase in self-regulatory ability as measured by TM.

To further investigate the didactic element of the intervention workshop as the hypothesized mechanism of change, students self-reported knowledge in the domains targeted by the intervention were measured prior to attending the workshop and at the end of the course. Students' self-reported knowledge regarding multitasking's impact on learning and attention, precommitment strategies, decision fatigue, and the Pomodoro technique had increased significantly more in the intervention group when compared to the change in knowledge reported by the control group. With regard to the concept of ego depletion, students' self-reported knowledge in this domain increased significantly both in the intervention and control groups, with no significant differences in the magnitude of change between groups. This is likely due to either the fact that students were enrolled in an introductory psychology course and the concept of ego depletion may have been covered as part of the curriculum or discussed in the control groups.

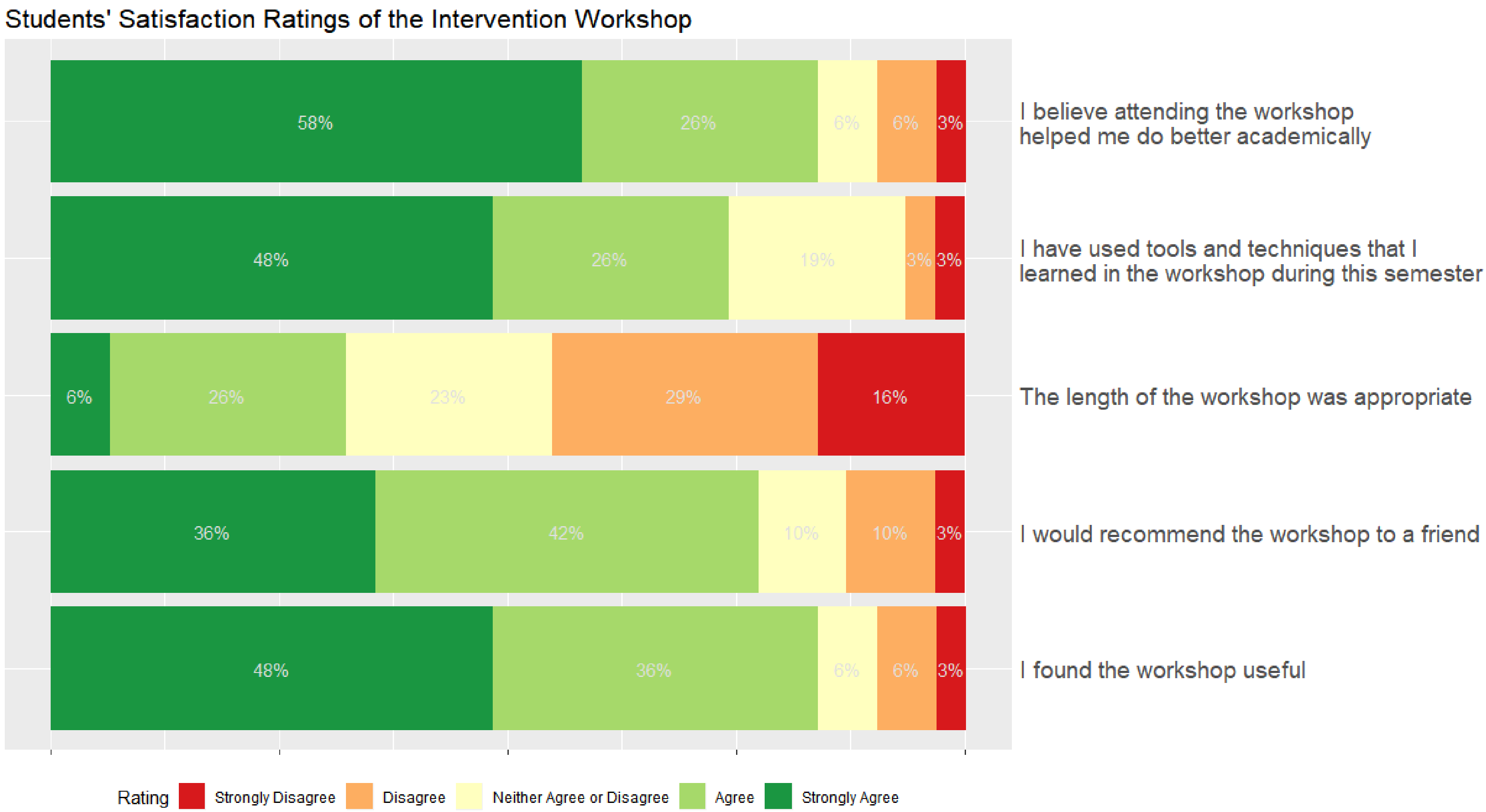

Figure 36
Student satisfaction and feedback regarding the intervention workshop.

Overall Discussion

The overarching aim of this research project was to build a theoretical foundation for self-regulation in emerging adulthood during the transition to university, and to build a time-management intervention informed by that framework to assist students who would otherwise struggle in traversing the post-secondary journey. Attending university for the first time involves a stressful transition for most youth, with a substantial minority of students experiencing serious difficulties and failing to complete their degrees (Pantages & Creedon, 1978; Wintre & Yaffe, 2000; Wintre & Bowers, 2007). To provide a framework for understanding self-regulation and development during this period, we proposed the Regulation Extension to Sameroff's Unified Theory of Development (RESUTD).

Sameroff made use of a concept from evolutionary theorists Gould and Eldredge (1977) who labelled periods of rapid change as *punctuated equilibrium,* when large changes in the environment or the person push development towards new states of equilibrium. We posited that the transition to university within the context of emerging adulthood is one such case of punctuated equilibrium when the individual must adapt to demanding internal and external changes. In this context, how well students regulate their behaviour to meet academic demands decides the success of their adaptation to this transition.

We built on Sameroff's (2010) regulation model and its insight regarding the importance of other-regulation. Self-regulation happens within a context, a social surround that is actively engaged in "other," even in the case of emerging adults who are increasingly more independent. Most emerging adults remain only semi-autonomous, continuing to rely on parents and institutions (e.g., university, military) to scaffold their prolonged entry into adulthood (Arnett, 2006; 2012). As the range of other-regulators can comprise more than other individuals, we constructed the term *external-regulation* to replace *other-regulation* to better reflect this concept and its corollaries with regards to the use of environmental tools for the regulation of behaviour. In Sameroff's regulation model (Figure 2), the sum of behaviours being regulated is portrayed to be constant, divided between self-regulation and external regulation. We extended this model so that it could apply to situations where the regulatory demand on the individual varies, through the addition of the concept *behavioural space* (Figure 4). Finally, we proposed the addition of a concept depicted in Figure 5 as "entropy" which illustrates the failure or lack of regulated behaviour (either internally or externally) with regard to the behavioural demands of a particular activity or goal.

The objective of the first study was to use a longitudinal design with a sample of emerging adults transitioning to university in order to test the proposed RESUTD model. Self-regulation in the academic context was operationalized in the longitudinal study through a questionnaire that measured various self-initiated behaviours. important to time-management at university. External regulation within the academic context was operationalized through a questionnaire that measured students' perceptions of the structure and support that their university environment provided for them. The effects of entropy were conceptualized as resulting in lower levels of adjustment to university, and higher levels of mood and anxiety challenges.

The analyses revealed a significant and notable impact of pre-existing student attributes, including SES, high school graduating average, and gender, even in the context of average self and external regulatory resources. The consequences of these pre-existing student characteristics on the trajectories of adjustment and psychological well-being behoove the university to implement effective supports, including psychoeducational interventions, to level the playing field for at-risk students. The results of the study further demonstrated the important role, and consistent influence, of both internal and external regulatory resources on student adjustment to university and emotional well-being outcomes. In particular, it was noted that students who do not have adequate self-regulatory skills during the first year and who also do not receive adequate external-regulation experience adjustment and emotional difficulties. Therefore, to help these students, the university should provide not only support and structure but also interventions that develop the internal regulatory skills of the student.

The Imperative of Self-Regulation Interventions for Post-Secondary Students

The negative outcome associated with inadequate self-regulatory skills that were demonstrated in the longitudinal study of students transitioning to university is corroborated by research demonstrating that many institutions experience up to a quarter of their first year students not returning to continue their studies for a second year, with negative economic and social consequences for both the institution and student (Duckworth, Taxer, Eskreis-Winkler, Galla, Gross, 2019). Students who do not persist into their second year of studies often have lower self-regulatory skills such as excessive procrastination, poor time-management skills, and being distracted in the classroom (see Stelnicki, Nordstokke, & Saklofske, 2015, for a review). The self-regulatory deficit that students face is exacerbated by frequent multi-tasking and its adverse consequence that were previously discussed at length. For example, in a naturalistic at-home investigation of studying, students aged 12 to 24 averaged fewer than 6 minutes on the task before an interruption involving texting, or checking their social media accounts (Rosen, Carrier, & Cheever, 2013). The critical influence of self-control on course grades explains why grades predict college persistence and graduation better than do standardized achievement test scores (Bowen, Chingos, & McPherson, 2009).

The importance of self-regulatory skills is magnified by research indicating a trend of students devoting less time to their studies (Nonis & Hudson, 2010). In this context, *how* students study may be more important in terms of their academic and socio-emotional outcomes than how much they study (Rau & Durand, 2000; Nonis & Hudson, 2010). Time-management interventions that enhance students' ability to self-regulate to meet their academic challenges have shown that they not only improve student grades and academic outcomes, but also reduce student stress (Häfner, Stock, & Oberst, 2015).

In designing the time-management intervention for the second study, we aimed to not only provide psychoeducation about the challenges posed by digital media, multi-tasking, and studying habits, but also provide practical tools and strategies that students could put into practice. The focus of these strategies was to bolster the students' internal and external regulatory resources through both enhanced awareness of optimal behaviours, and the use of strategies that can modify the students' environment. These strategies included the concept of precommitment which bolsters behavioural regulation through the modification of the environment and by reducing the reliance on in the moment inhibitory control. Previous studies have shown that when a situation demands two consecutive acts of self-regulation such as inhibiting an impulse or resisting temptation, performance on the second act is frequently impaired (Muraven & Baumeister, 2000).

These research findings suggest that, depending on the context, it may be even more optimal to rely on external-regulatory aids than to overwork internal resources to regulate behaviour towards a goal (Milkman, Rogers, Bazerman, 2008). The classic example of a pre-commitment strategy is in the story of the Odyssey by Homer, where Odysseus, on his sail home from the Trojan war had to pass the island of the Sirens. The Sirens sang an alluring, magical song that was irresistible to the sailors and resulted in their ships hitting the island's rocks. Odysseus wanted to hear the song, but to avoid the temptation the song presented, he plugged his sailors' ears with wax and ordered his men to tie him up, so he wouldn't take control of the boat and drive it into the rocks. When Odysseus heard the song, he tried to break free from his ropes and steer the ship into the rocks, but the ropes held him, and the ship safely sailed past (Elster & Jon, 2000).

The strategy of pre-commitment, which involves students committing to decisions in advance of their implementation, combats present bias, the tendency to dramatically overweight immediate rewards relative to gains. Pre-commitment combats present bias by ensuring that at the time of a decision regarding whether to engage in a valuable, future-oriented behaviour (e.g., studying for an exam), the long-term benefits of that behaviour are not discounted, and short-term costs are not exaggerated (see Milkman et al. 2008 for a review).

Pre-commitment strategies offer an alternative to in-the-moment effortful acts of willful inhibition, by modifying one's future available options and temptations (Studer, Koch, Knecht, & Kalenscher, 2019). This is accomplished, for example, by removing tempting, but less desirable choices relative to long term goals (e.g., blocking access to social media prior to starting the study session), and/or adding unattractive consequences to such alternatives that inflate their costs (e.g., having to pay a fine, see StickK[1], goal-setting apps that offer real-world punishments for failing to meet your commitments). Outside of the digital realm, an example of a precommitment strategy is CapturedDiscipline,[2] a solid-steel safe that can be locked for a previously decided duration of time for managing temptations such as chocolates or cigarettes. A similar idea involves using bank safety deposit boxes as a means of imposing a moratorium on

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[1] http://www.stickk.com/
[2] https://www.captureddiscipline.com/

credit card use. Research has demonstrated that precommitment strategies raise retirement saving rates, chances of smoking cessation, healthy food shopping, and choices of delayed rewards over instant gratification (see Studer et al., 2019, for a review). In the present intervention workshop, students were provided with psychoeducation regarding ego depletion and pre-commitment strategies and provided tools such as the program called "Freedom" which allows you to turn your computer's Internet access off for a predetermined period of time[3]. Students were also taught the importance of pre-planning their study routine, to mitigate decision fatigue. Pre-planning serves as another form of pre-commitment, albeit with less rigidity, and can enhance both self-regulation and the students learning achievements (Hao, Maribe Branch, & Jensen, 2016).

Collectively, the strategies that were utilized in the time-management intervention workshop work to reduce the entropy caused by a sudden reduction in external regulation as students transition from structured academic environment of the high school to the far less externally regulated educational experience of university. These strategies were successful in helping students enhance both their self-regulated and externally regulated behaviours to meet the demands in their academic behavioural space. This success was evident in the results of the program evaluation which showed attending the intervention group was predictive of higher grades and academic adjustment scores, as well as lower perceived stress ratings. Further analysis indicated that the key ingredient driving the improved outcomes for students was the increase in time-management ability.

[3] https://freedom.to/

Impact and Implications

Given the importance of time-management skills to student success, and the success of the time-management intervention, the Vice Dean of Teaching in the Faculty of Health invited a follow-up to the workshop in the form of digital video modules to be intergraded as part of the orientation of first-year students at York University. Digitization of the workshop allowed the content to be more widely and easily disseminated. Building on the results of the program evaluation, and in particular, the satisfaction feedback provided by the students (see satisfaction survey results presented in Figure 36), the video modules were made shorter in duration. The workshop was divided into three video module series entitled "#StudyHacks" and hosted on the YouTube[4] streaming platform.

The effectiveness of the online video-based time-management intervention series was evaluated as part of the First Year Experience at York University. The program evaluation was led by a post-doctoral researcher, Dr. Jerusha Lederman, through the York University Teaching Commons. As part of the program evaluation, the #StudyHack video series was shown in 15 first year introductory courses, including those offered by the departments of Biology, Chemistry, Physiology, and Psychology, reaching a total of approximately 6140 students (Lederman & Baker, 2017). Of these students, approximately 1200 completed questionnaires that examined a number of outcomes including their emotional well-being, attrition risk, the change in their knowledge regarding key concepts covered in the video modules.

Students in classes that were exposed to the #StudyHack video interventions were provided with an opportunity to give feedback on their knowledge of key concepts prior to watching the videos. Students across programs indicated by a large margin that they were not

[4] youtube.com/playlist?list=PLAtpGLsFf0AxXVQFNsDCzozsbQGVCg49Z

aware of the key concepts (e.g., Pomodoro technique, the impact of multitasking on attention and memory, precommitment strategies, ego depletion, decision fatigue) that the intervention targeted (Lederman & Baker, 2017). Furthermore, after watching the videos, students reported a significant change in their knowledge across all concepts presented in the series. The #StudyHack intervention appears to lead to significant change in first-year students' knowledge of key concepts targeted by the intervention. The researchers also uncovered a significant interaction between the intervention and attrition risk with regards to stress levels. Students who were at risk of attrition appear to benefit significantly more from exposure to the #StudyHack videos with those who had reported watching at least one of the #StudyHack videos reporting significantly less perceived stress, bringing them on par with their low risk of attrition peers. Overall, first-year respondents found the #StudyHack video modules helpful with over 75% of students finding all three videos helpful.

Based on the results of the program evaluation, the video series was added to the York University's First Year Experience portal[5] to be used in first-year courses and as part of student orientation.

Strengths, Limitations, and Future Directions

The first study in the present research project had a number of key strengths, including the longitudinal nature of the research design, the multiple university sites, the complex analyses that allowed for the examination of important developmental processes over time, and the large sample size that facilitated the investigation. It is the first known study to longitudinally examine self-regulation through emerging adulthood. Similarly, it is the first study to use a longitudinal design to investigate Sameroff's (2010) self-regulation model. Although the importance of self-

[5] http://fye.yorku.ca/

regulatory skills (i.e., time-management) during the university transition has been examined by a number of researchers, the development of self-regulation, and the influence of support and structure from the institution scaffolding this development, have not been previously longitudinally examined.   The study was rooted in a developmental theoretical framework and used a large sample size across multiple and diverse settings to examine the utility and validity of its theoretical constructs. The results provide actionable recommendations for post-secondary educational institutions to address the key need for improved self-regulation of their emerging adult student populations, which have been shown to reduce psychological distress as well as increase academic adjustment.

In Study Two, we built on the insights gleaned from the theoretical self-regulation model that we had tested in the first study to design a time-management intervention. The main strengths of the second study included the intervention being rooted in a tested theoretical model informed by the scientific literature to address the key needs of first-year students. This intervention was evaluated using a rigorous randomized design with an active-placebo control group with pre and post data collection, including objective measures such as course grade outcomes. The rich theoretical framework and rigorous evaluation of the time-management intervention allow us to offer it to the post-secondary community as an evidence-based intervention for emerging adults transition to university. In fact, follow up projects drawing from these finding have already shown promising results and have helped thousands of first-year students at York University (see #StudyHacks video series and its independent evaluation by the faculty of Health at York University discussed in the previous section.)

Despite the strength of the two studies in this project, there are several limitations that should be noted. First, and perhaps most importantly, the first study sample incurred notable attrition over the three years of data collection. Although the statistical method used allowed for the use of any data available, it would be informative to inquire as to the reason for the attrition (discontinuing the study versus dropping out of university). Even in the case of the students who discontinue because of leaving the institution, there is evidence that many transfer to another institution that provides a better fit or return after a hiatus, all of which could be discerned by follow-up contact (Wintre & Morgan, 2009). Similarly, in the second study, four individuals discontinued from the study before the final data collection. Ideally, any future replications of the intervention or longitudinal design would incorporate an exit interview where participants' reasons for discontinuation are explored.

The intervention time-management study, despite its rigorous randomized evaluation design, had a number of limitations. The most notable is the lack of follow-up to examine whether the gains are maintained, and to see the trajectory of the intervention versus the control group further diverge in terms of psychological well-being or academic outcomes. Replicating the time-management intervention with a longitudinal follow-up data collection would be a fruitful future research project. Such a follow-up design may also investigate the latent effects of the intervention. For example, given the difference in perceived stress scores between the control and intervention groups, it is possible that with further time depression ratings would have also diverged, due to the predictive influence of stress the occurrence of depression in emerging adults (Sheets & Craighead, 2014). Finally, follow-up data collection would also inform the intervention design as to whether booster sessions are required to maintain gains.

The evaluation process should also be replicated, with the inclusion of a passive-placebo control group (e.g., a waitlist condition) that would allow measuring the impact of attending the time-management intervention relative to the typical first-year student experience. With regard to the intervention study, another limitation, and opportunity for future research, is to take into account extraneous demands on the students' time, such as part-time employment, commute time, or caregiving responsibilities. It is possible that improved time-management skills differentially benefit those under a greater time constraint. Another direction for future research would be to investigate the finding in the longitudinal study that female students not only had a higher initial level of time-management but also had a positive slope, indicating that their self-reported time-management skills increased as they progressed through the important early semesters as compared to their male peers.

Finally, a promising area of research that could further extend the intervention design and content is to add a social component to pre-commitment strategies. Precommitment strategies can be used in a social context as demonstrated with research on individuals recovering from addiction. Money management often is a significant challenge for individuals recovering from addiction. In an intervention developed by Rosen and colleagues (2010), individuals who are recovering from addiction are assigned a money manager who also serves as a supportive coach, and they agree to deposit their money in an account that only their coach can access. The coaches also help clients set goals and priorities and provide each client with only enough money to cover their planned and agreed-upon expenses. To make an unplanned purchase, the client would need to fill out a formal request that could be delayed by 2 days if it is not consistent with the client's stated goals, or if the manager suspects the client is intoxicated. In this way, the client cannot act on impulses. The intervention has proved successful not just in helping individuals recovering from addiction manage their money, but also at reducing substance use (Rosen, Rounsaville, Ablondi, Black, & Rosenheck, 2010). This idea can be expanded in the academic context by providing "Willpower Coaches" to students, who can for example "hold on" to the student's passwords for gaming accounts, social media, media streaming websites (e.g. Netflix) until the end of the exam period or some pre-arranged agreement by the student.

The exciting research presented in the present paper, including the RESUTD model and the time-management intervention, addresses and provides a starting step to ameliorate a major challenge facing emerging adults in the 21st century during their transition to post-secondary studies. Furthermore, evidence of its tangible impact, alongside the positive feedback received from the student and staff regarding the benefits of the developed intervention, has provided us with the motivation and energy to continue to refine this line of research and test its application to other contexts such as the workplace.

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Appendix A: Study One Statistics

R Software Version and Packages

R software version 3.4.4 (2018-03-15) was used, and packages used for the analyses included:

```
attached base packages:
[1] grid      parallel  stats     graphics  grDevices utils     datasets
[8] methods   base

other attached packages:
 [1] magrittr_1.5       plyr_1.8.4         gridExtra_2.3
 [4] pander_0.6.2       stargazer_5.2.2    predictmeans_1.0.1
 [7] lme4_1.1-18-1      Matrix_1.2-12      stringr_1.2.0
[10] piecewiseSEM_1.2.1 nlme_3.1-131.1     ggplot2_3.0.0
[13] reshape2_1.4.2     lattice_0.20-35    car_3.0-2
[16] carData_3.0-1      tidyr_0.6.3

loaded via a namespace (and not attached):
 [1] lavaan_0.6-2      tidyselect_0.2.4  purrr_0.2.5       splines_3.4.4
 [5] haven_1.1.2       colorspace_1.3-2  stats4_3.4.4      yaml_2.1.14
 [9] rlang_0.2.2       nloptr_1.0.4      foreign_0.8-69    glue_1.3.0
[13] withr_2.1.2       readxl_1.1.0      bindrcpp_0.2.2    bindr_0.1.1
[17] munsell_0.5.0     gtable_0.2.0      cellranger_1.1.0  zip_1.0.0
[21] labeling_0.3      rio_0.5.10        forcats_0.3.0     pbkrtest_0.4-7
[25] curl_3.2          Rcpp_0.12.18      scales_1.0.0      abind_1.4-5
[29] mnormt_1.5-5      digest_0.6.16     hms_0.4.2         stringi_1.1.5
[33] openxlsx_4.1.0    dplyr_0.7.6       numDeriv_2016.8-1 tools_3.4.4
[37] lazyeval_0.2.1    tibble_1.3.3      pbivnorm_0.6.0    pkgconfig_2.0.2
[41] MASS_7.3-49       data.table_1.11.4 assertthat_0.2.0  minqa_1.2.4
[45] R6_2.2.2          compiler_3.4.4
```

Cohort Analysis

Of the initial 2887 participants who provided demographic information prior to attending university, 1075 were in the 2004 cohort, and 1812 were in the 2005 cohort. Comparing the attributes of the two cohorts revealed a significant difference between the gender proportion of students who participated in the 2004 and 2005 data collection cohorts, with a lesser proportion of male participants in the 2004 cohort, $\chi^2(1) = 33.37$, $p < .001$. The initial 2004 cohort sample included 404 male and 671 female participants, and the 2005 cohort sample included 877 male and 923 females. There were no significant differences between the self-reported income distributions of the two cohorts, $\chi^2(3) = 7.64$, $p = .05$. Students from the 2004 cohort had a higher average self-reported high school graduating GPA (M = 83.77) than the 2005 cohort (M = 82.86), $t(2311) = 3.6$, $p < .001$. Finally, a greater proportion of students from Memorial University constituted the 2005 cohort sample as compared to the 2004 cohort, $\chi^2(5) = 79.41$, $p < .001$.

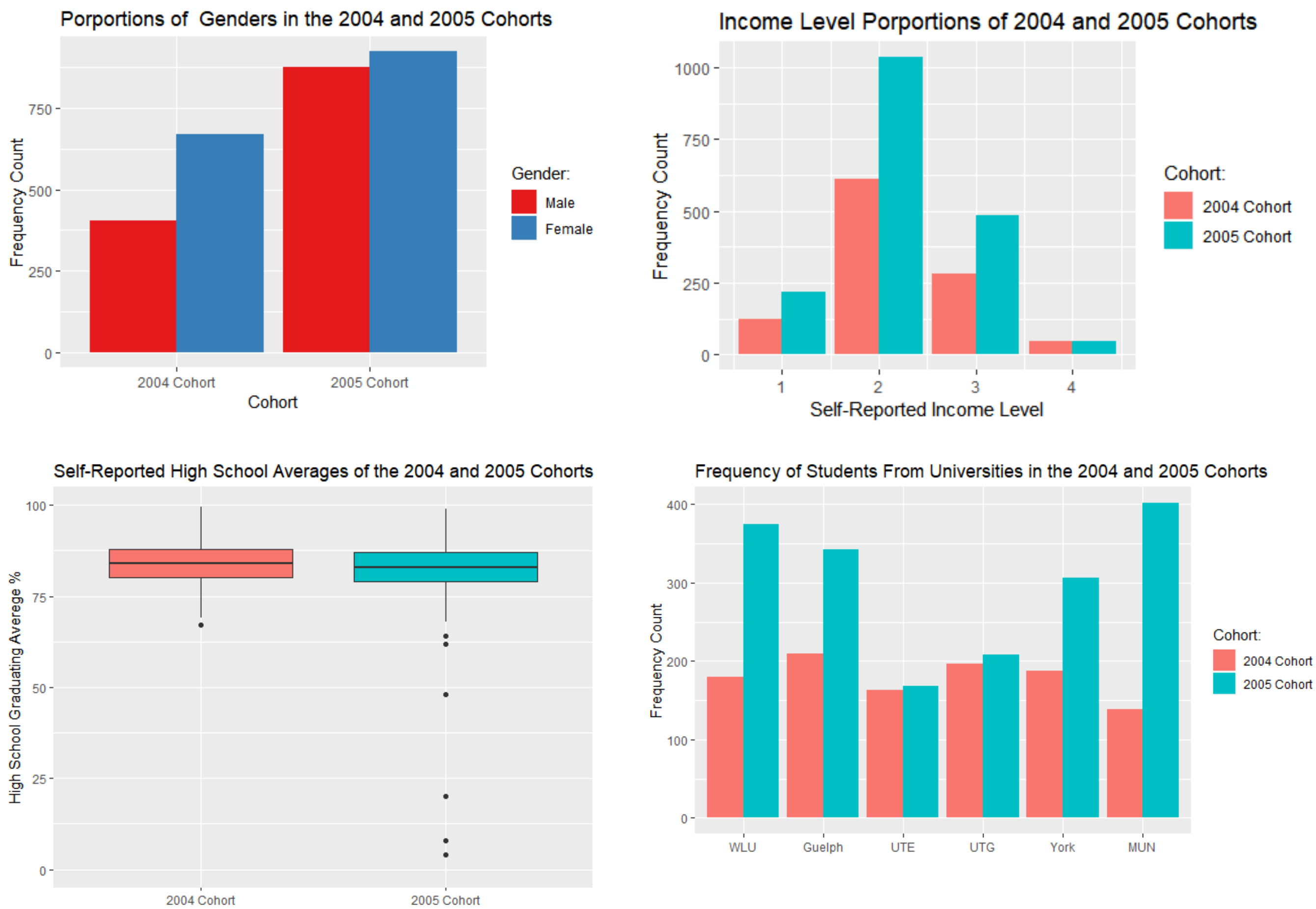

Figure 37
Demographic Attributes of the 2004 and 2005 Cohorts

Screening for Random Responders

The data from the 1400 participants were screened for careless or random responders. Careless and random responding patterns were a concern since participants were given incentives to participate in the study and after the initial demographic survey in August, all subsequent questionnaires were done through the internet. Prior studies have shown evidence of nonnegligible random responding in samples of undergraduate participants (Meade & Craig, 2012). Furthermore, when data are gathered through online surveys, there is the possibility of responders multi-tasking or engaging with distractions that result in divided attention and careless responses (de Rada & Domínguez-Álvarez, 2014). Random and careless responses typically have mean scores around the midpoint of a measure's response range, which reduces the mean score variance resulting in decreased power and increased Type II errors (Credé, 2010; Osborne & Blanchard, 2011; Holden, Wheeler, & Marjanovic, 2012).

ISD is an index that discriminates between conscientious and random responders by using an individual's response variance for each of the instruments used in the questionnaire battery. This is an effective way to discern random responders who typically answer items without regard for what the items mean and as such their scores across items, including reversed items, will have greater variance (i.e., be less correlated). Conversely, conscientious responders respond similarly to items that tap into the same psychological construct, and therefore their responses will vary less across the breadth of the response scale. This results in conscientious responders having smaller ISD scores whereas random responders produce larger ISD scores (Marjanovic et al., 2015).

The ISD was calculated for each participant's response pattern on the SPUSS, TM, SACQ, and CES-D scales. These scales were chosen as they each contained over 20 converging items, as such a large ISD would be indicative of careless or random responding. Participants who had a high ISD on multiple scales (defined as 1.5 times the interquartile range for that scales distribution of ISDs) were flagged for further investigation. Five participants who had high ISDs on multiple measures or on multiple measurement points were excluded from further analysis

(Participants with IDs of 21, 1273, 1303, 1830, 1884). The final sample size prior to MLM analysis included data from 1395 participants and 3189 observations in total across time.

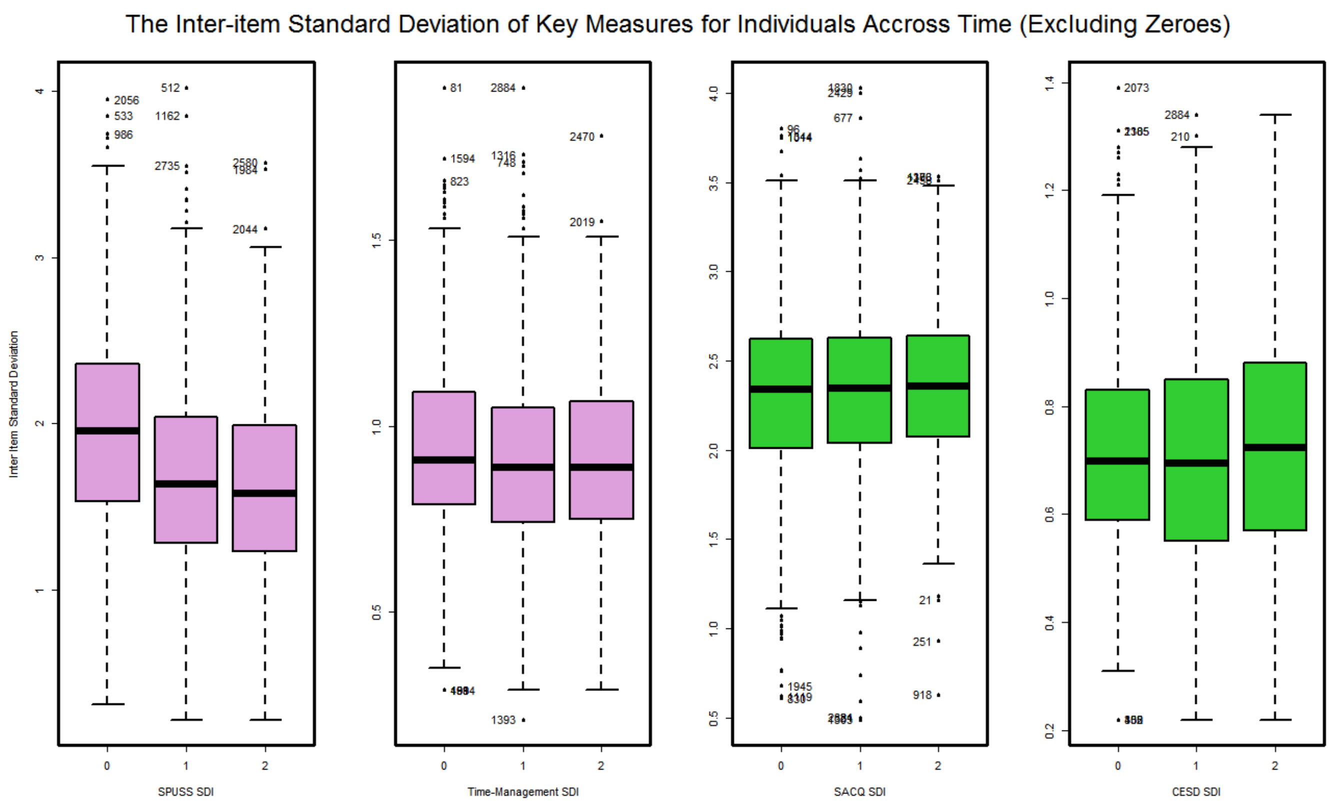

Figure 38
The ISD of selected variables in Study One.

Research Design and Analysis Using Multi-Level (Mixed) Models

There are many instances where human data typically found in social sciences have a cluster or hierarchical structure. For example, siblings with the same parents tend to be more alike in their physical and mental characteristics than individuals chosen at random from the population at large. Individuals could further be nested in multiple hierarchic structures, such as classroom, school, district, province, etc. Another important form of clustering which may not be intuitively apparent at first is data gathered from the same individual over various time periods.

Multilevel data structures arise in longitudinal studies where an individual's responses over time are correlated with each other (Singer & Willett, 2003).

Multilevel models recognize the existence of such data hierarchies by allowing for residual components at each level in the hierarchy. For example, in a longitudinal study of post-secondary student attrition, a two-level model would allow for grouping of a student's data points over time and students between various universities that they attend. Thus, the residual variance is partitioned into a between-university component (the variance of the university-level residuals) and a within-university component (the variance of the student-level residuals). The university residuals represent unobserved university characteristics that affect student outcomes. It is these unobserved variables which may lead to correlations between outcomes for students from a shared environment such as attending a specific university.

The repeated-measures ANOVA-based analyses can be viewed as special cases of multi-level models (MLM) (Singer & Willett, 2003). Hence, MLM can employ these same analytic strategies for simple within-subjects designs, but it also provides several advantages over ANOVA in terms of handling missing data and flexible modelling of variance-covariance structures. MLM also offers a unique data analytic strategy for within-subjects designs that is not possible when using ANOVA. Namely, MLM can be used to model individual-level trends over time, referred to as individual growth models, in which trajectories can be estimated for each participant (rather than simply average trends). In traditional repeated measures ANOVA, individual growth models are not estimated; rather, an average growth model is estimated in a single analysis of all participants, and individual variation around the average model is treated as error (Singer & Willett, 2003).

Another key difference between MLM and traditional repeated measures ANOVA is in the estimation of parameters. ANOVA uses least squares (LS) estimation, whereas, in MLM, maximum likelihood (ML) is one of the commonly used estimation methods. The use of ML estimation allows easy treatment of missing data, as all available data points can be used (Singer & Willett, 2003). Missing data are often a reality with longitudinal studies; therefore, MLM's ease of handling missing data is a great advantage. Another advantage of MLM is in the treatment of the time predictor, which is treated as a continuous variable. Because of this, MLM can accommodate unequal spacing between time intervals and unbalanced data. Observations may be collected at unequally spaced intervals (e.g., measurements collected 1 month, 4 months, 7 months, 1 year, 5 years following treatment). Observations may also be collected at different time points for different participants (e.g., for the first participant 0, 2, 4, 8, months following treatment; for the second participant 1, 5, 10, 12 months following treatment). Such patterns of observations may occur because of practical problems in implementing the original data collection design. Unbalanced data and unequal spacing conditions can be flexibly handled under MLM through adequate specification of the time predictor.

An advantage of MLM is that it can make use of all available data in the estimation of model parameters due to its flexible treatment of the time predictor (Singer & Willett, 2003). A research participant with only baseline data can be included in the analysis and contribute to the estimation of model parameters. The validity of using all available data does depend on whether missing data are *missing completely at random* (or *missing at random*, which is a less restrictive missing data assumption). Additionally, the treatment of time as a continuous instead of discrete variable in MLM can increase the statistical power for detecting the growth effects (Singer & Willett, 2003).

ANOVA and MLM also differ on the statistical assumptions related to the variance-covariance structure when analyzing longitudinal data. In repeated-measures ANOVA, the variance-covariance matrix of observations taken over time is assumed to meet the requirements of sphericity. Compound symmetry, which is sufficient to fulfill the requirements of sphericity, implies that the variances of measures at each time period are equal, and also that the covariances between all pairs of time periods are equal. This is a strong assumption and is likely to be unrealistic for most longitudinal studies. Violations of the assumption of sphericity can lead to incorrect decisions in ANOVA-based analyses. In MLM, there is great flexibility in specifying the variance-covariance structure of longitudinal data such as a general "unstructured" variance-covariance assumption in which every variance and covariance is free to be estimated from the data or more restrictive assumptions that still include autocorrelated structures, in which covariances are a function of distances between time periods, and variances can be modelled as either homogeneous or variable (Singer & Willett, 2003).

Finally, MLM easily incorporates covariates, which can be used in research for different purposes such as to statistically control participants on some variable of interest or to find mediators of the relationship between time and an outcome variable (Singer & Willett, 2003). In repeated-measures ANOVA, all covariates in a model must be time-invariant. Using MLM, in contrast, the researcher can include time-varying covariates in an analysis. Time-varying covariates are often assessed concurrently with major outcome variables and can change over time for each participant.

Multi-Level Model Selection

Using multi-level modelling for longitudinal data allows us to estimate individual trajectories, including intercepts and slopes, as well as group estimates and differences therein.

Prior to the process of statistical model building, it is important to inspect the data for suitability of being modelled, including noting any non-linear patterns and assessing the presence of sufficient variability over time. Plotting individual-level data can also be used to flag unusual levels or trajectories for individual participants (Kwok, Underhill, Berry, Luo, Elliott, & Yoon, 2008). The empirical-growth plots for each outcome variable are presented prior to discussing the model results.

Further assumptions of the selected model were examined both visually and through statistical tests, and the results are presented in Appendix B. These assumptions include: 1) the error terms at every level of the model are normally distributed 2) homoscedasticity, i.e., equality of residual variance for both intercept and slope terms at each level of the predictor variable (or the use of appropriate variance-correlation matrix) 3) independence of observation, indicating that cases are random samples from the population and that scores on the dependent variable are independent of each other.

Model Selection Process. Model selection was started by building a simple random intercept model for calculating interclass correlation (ICC) and a simple linear growth model, followed by a model with time-invariant controls and time-variant process variables. These models were compared for fit at every step of the selection process.

The first model computed is the Unconditional Means Model, which does not include any predictors for either the intercept or the slope of trajectories. This model estimates the grand population mean (γ_{00}), and residual terms for within-individual (σ_e) and between-individual (σ_0) variation. These residuals provide information on the amount of variability available to be predicted by other variables that will be added to the model. The p-value of the intercept is not meaningful at this point (essentially conveying that is different from zero). It is, however, meaningful to know if the within and between individual residuals differ from zero, noting the usefulness of adding further predictors.

The Unconditional Means Model is also used to calculate the ICC. The ICC is the correlation between two observations within the same cluster. The higher the correlation within the clusters (i.e., the larger the ICC) the lower the variability is within the clusters and consequently the higher the variability is between the clusters. Calculating the ICC allows us to estimate the proportion of total variation in the outcome that lies between people and is hence worth exploring (Singer & Willett, 2003).

The Second model computed is the Unconditional Growth Model which includes time without any grouping predictors at the intercept or slope. Here, with the addition of time (i.e., academic year: $\gamma_{10)}$, we can see what portion of within-individual variation can be accounted for with the passage of time. The random effect σ_e refers to individual variation around their linear change trajectory, σ_0 refers to between-individual variability in intercepts, and σ_1 refers to between-individual variability in slopes. Finally, the intercept term γ_{01} refers to the estimate of the outcome measures (e.g., SACQ) mean at the end first year (the variable time is set to zero at the first measurement time-point, such that the intercept term could be meaningfully intercepted). This model also serves as a baseline for adding further predictors and allows the calculation of proportional reduction in individual residual when including linear growth (i.e., the amount of change that could be explained by time alone).

The next set of models that were constructed and compared add both time-invariant and time-variant predictors for the intercept and/or the slope estimates. These models are referred to as the Conditional Growth Models (or Conditional Models if the time variable is not retained) and explore the influence of process or group variables on the intercept and rate of change in the outcome measure.

To aid the interpretation of the intercept term, time-varying covariates have been centred. Under this condition, the intercept (time zero) refers to the estimated starting point for a male student (as gender was in binary terms for this dataset) with perceived below average SES and average scores on TM and SPUSS measures and an average high school graduating GPA.

Model Comparison. Model comparison was accomplished using a combination of statistical tools assessing fit, including the log-likelihood (LL) ratio test, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and R^2 measures.

The log-likelihood ratio test is defined by the following formula (also referred to as -2LL) $D = -2 * ln(\frac{\text{likelihood for null model}}{\text{likelihood for alternative model}})$ and the resulting test value (D) is part of a χ^2 distribution (Singer & Willett, 2003). Using the χ^2 distribution, the statistical significance between two models can be tested based on the difference D, the significance level, and the number of parameters different between the two models (Singer & Willett, 2003).

To avoid overfitting, a conservative alpha level (<.01) was chosen in comparing log-likelihood ratios. An overfit model is one that is too complicated for the sample data and becomes too tailored to fit the quirks and random noise in the specific sample rather than reflecting the overall population. Both goodness of fit measures, AIC, and BIC, penalize for model complexity relative to improved fitness, and therefore further reduce model overfitting. AIC penalty accounts for the number of parameters in the model and the BIC penalty goes further and also accounts for sample size (Singer & Willett, 2003). The general guideline for using these information criteria is to select the model with the smallest value on either AIC or BIC.

Variance Explained. In typical regression models, the coefficient of determination, better known as R^2, is a useful tool for describing the predictive capacity the model as it denotes total variance in the response explained by all the predictors in your model. R^2 has a number of useful properties. It is independent of sample size, ranges from zero to one, and dimensionless, which allows for comparison across different models. However, as a measure of model fitness, it can lead to overfitting because it almost always favours the most complex models. If the goal is to select among the best models, an information criterion approach (such as AIC or BIC) is preferred, because these indicators penalize for the number of predictors.

Unlike a typical regression model, MLM have multiple sources of residuals, such as from the intercept or slope terms, and therefore preclude an overall R^2. Sometimes researchers report the pseudo-R^2 statistic of the squared correlation between the fitted values provided by the model and observed values of the sample. It is important to note this is a pseudo-R^2 measure and must be interpreted with caution since the model fitted value is based on a mixed effects model that yields a fixed predictor estimates and variance associated with each random factor as well as the residual variance.

Nakagawa and Schielzeth (2013) provide an intuitive solution in the form of two easily interpretable values of R^2 that address the above issues. The first is called the *marginal R^2* and describes the proportion of variance explained by the fixed factor(s) alone. The fixed-effects variance is in the numerator, and the denominator is the total variance explained by the model, including the fixed-effects variance, the random variance and the residual variance:

$$R^2_{\mathrm{GLMM}(m)} = \frac{\sigma_f^2}{\sigma_f^2 + \sum_{l=1}^{u} \sigma_l^2 + \sigma_e^2 + \sigma_d^2}$$

The second is the *conditional* R^2, which describes the proportion of variance explained by both the fixed and random factors. The numerator contains both the variance of the fixed effects, as well as the sum of random variance components, while the denominator is identical:

$$R^2_{\mathrm{GLMM}(c)} = \frac{\sigma_f^2 + \sum_{l=1}^{u} \sigma_l^2}{\sigma_f^2 + \sum_{l=1}^{u} \sigma_l^2 + \sigma_e^2 + \sigma_d^2}$$

This method was extended by Johnson (2014) to include random slopes. Both the marginal and conditional R^2 are presented for each MLM model.

Checking Assumptions of MLM – SACQ

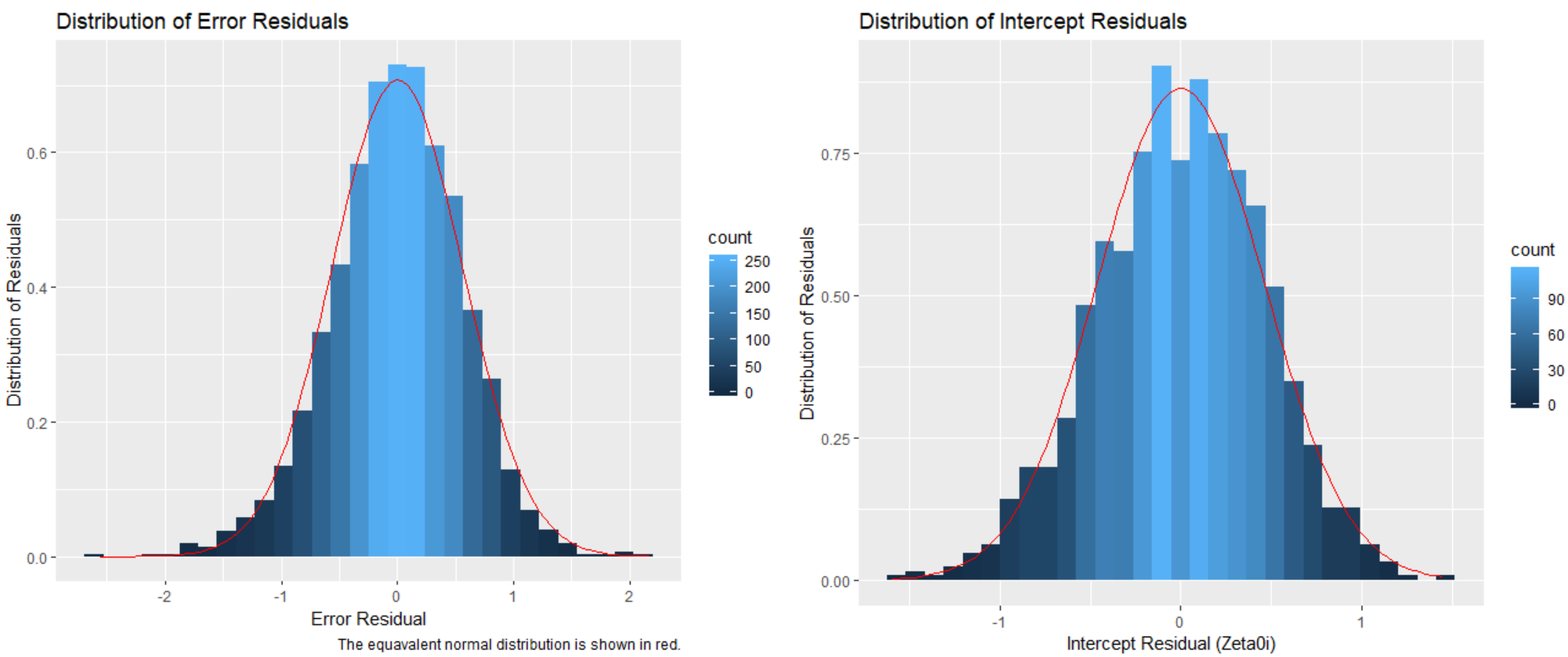

Figure 39
Distribution of error residuals in the MLM for the outcome of SACQ.

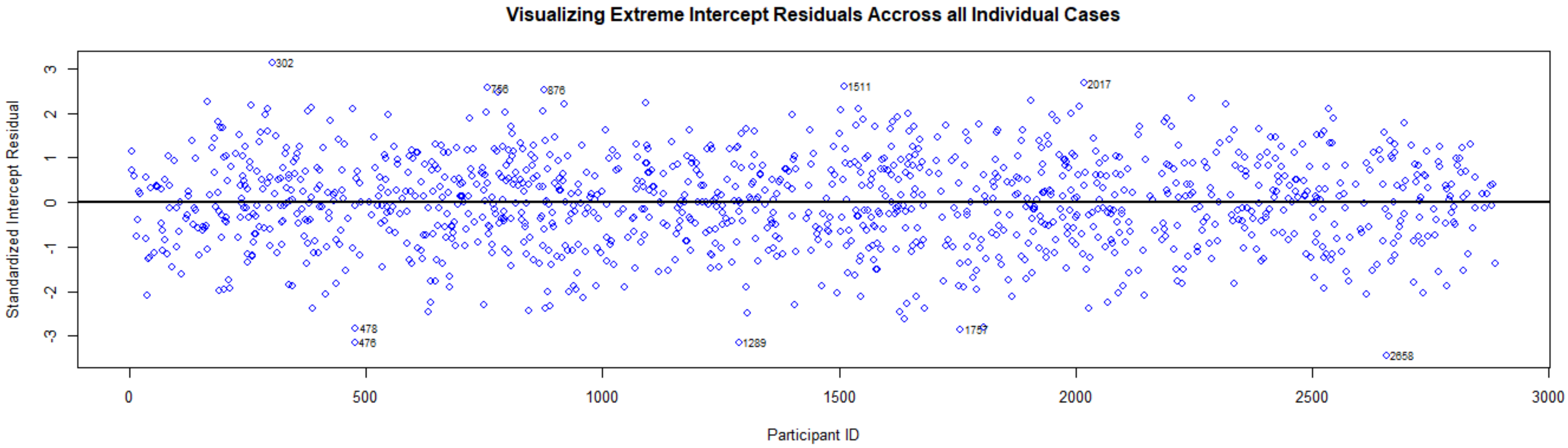

Figure 40
Visualizing extreme intercept residuals in the MLM for the outcome of SACQ.

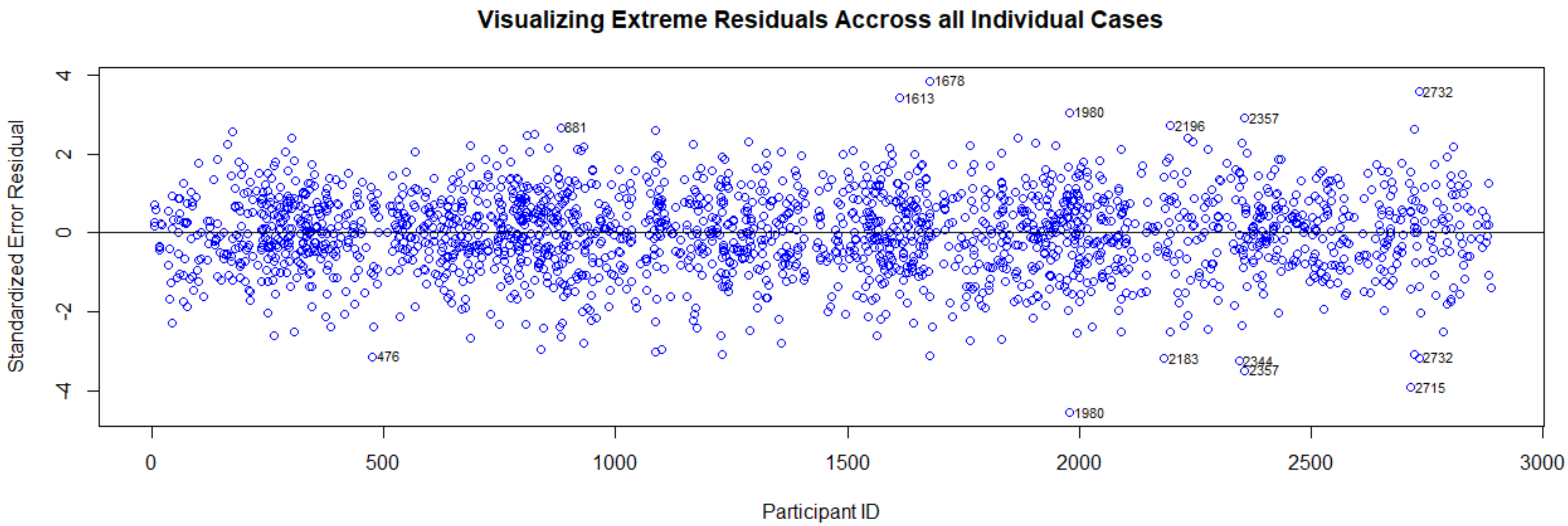

Figure 41
Visualizing extreme error residuals in the MLM for the outcome of SACQ.

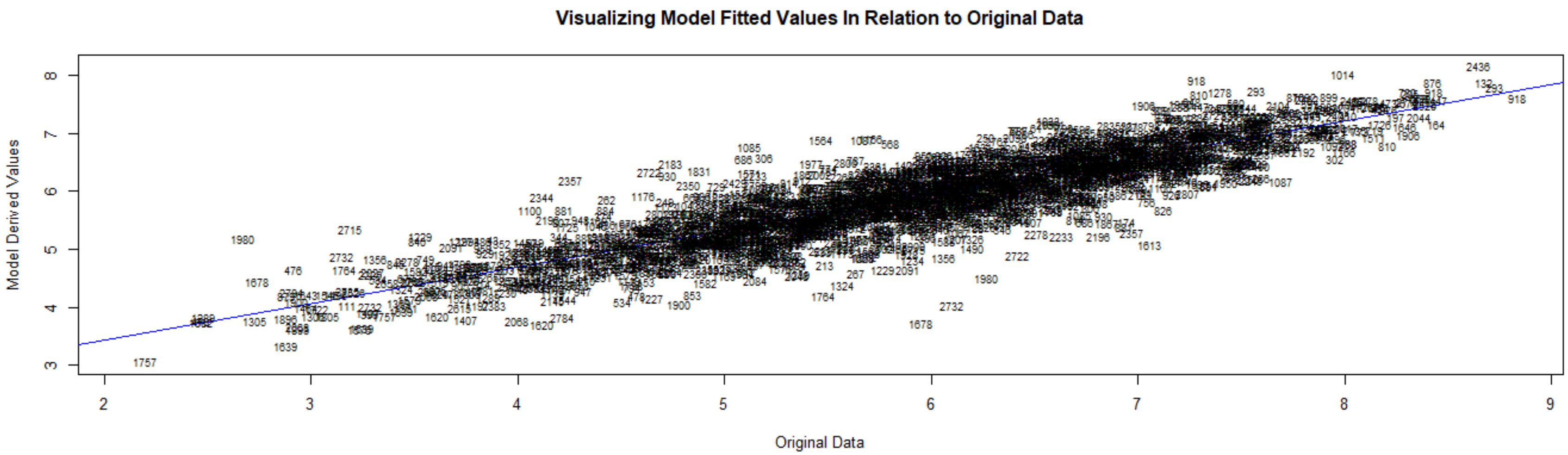

Figure 42
Visualizing model fitted values in the MLM for the outcome of SACQ.

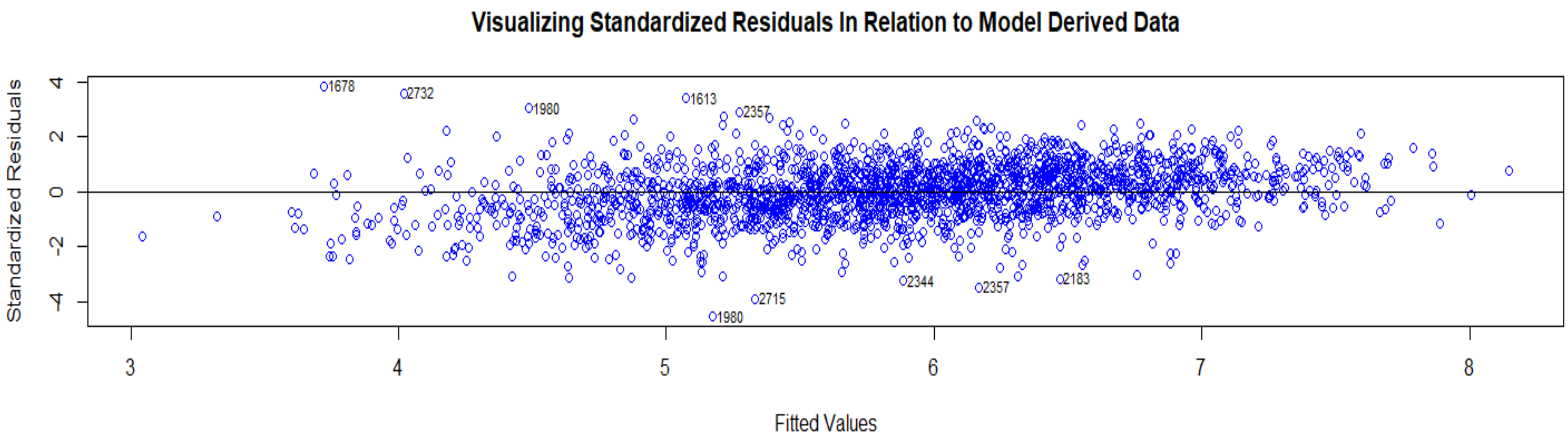

Figure 43
Visualizing standardized residuals in relation to model derived data in the MLM for the outcome of SACQ.

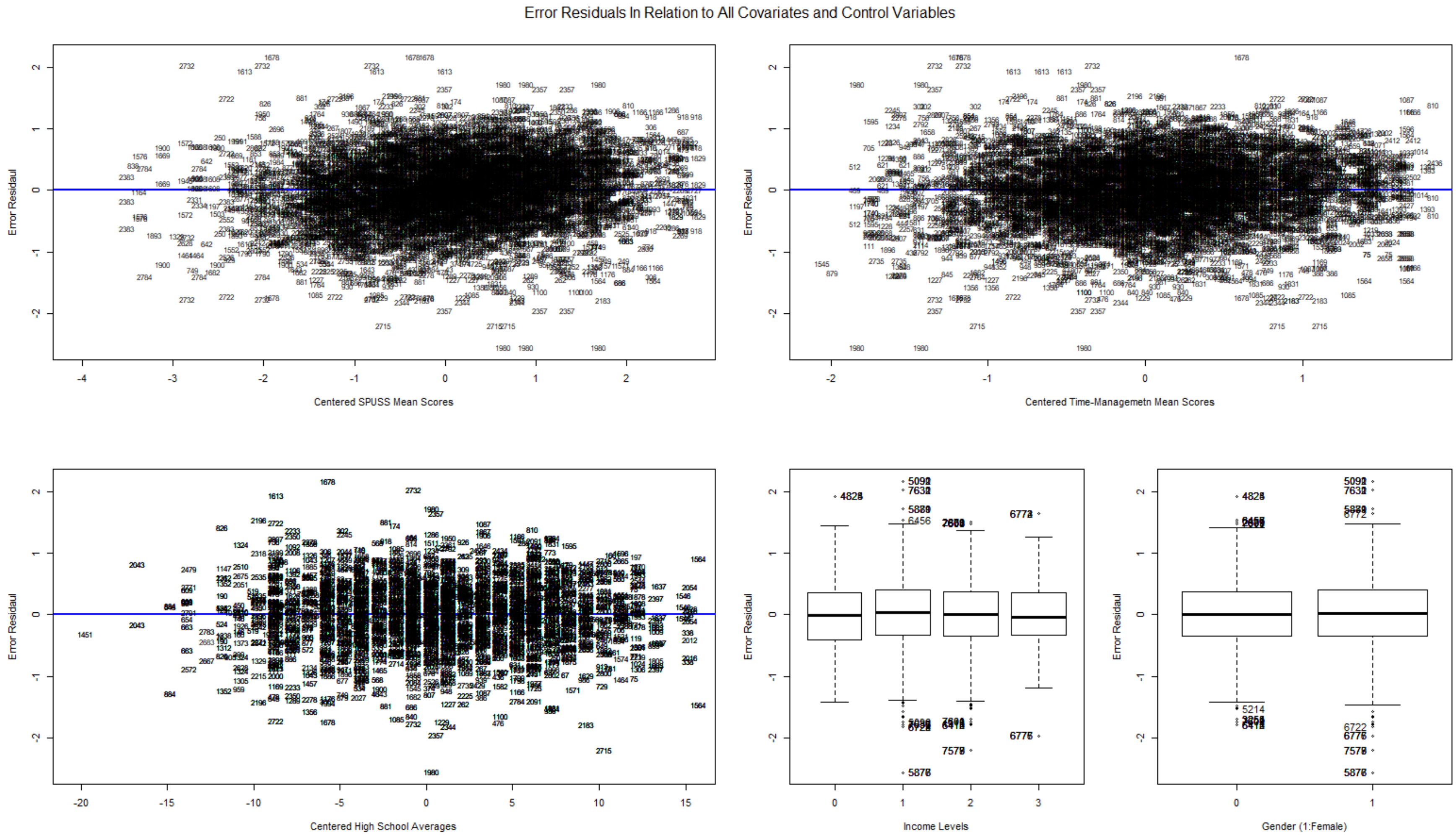

Figure 44
Error residuals in relation to all covariates in the MLM for the outcome of SACQ.

Table 23
Homogeneity of Residual Variance in the MLM for the Outcome of SACQ.

	df	F value	p
Levene Test Homogeneity of Residual Variance Across Genders	1, 5713	3.162	.075
Levene Test for Homogeneity of Residual Variance Across Income Levels	3, 5711	1.24	.29

Checking Assumptions of MLM – PSS

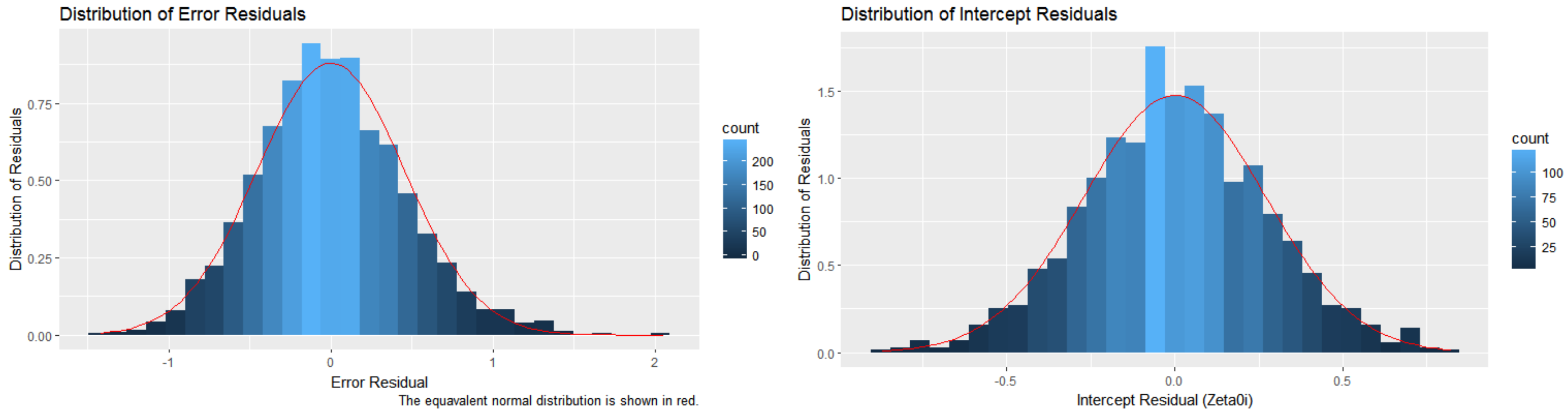

Figure 45
Distribution of error residuals in the MLM for the outcome of PSS.

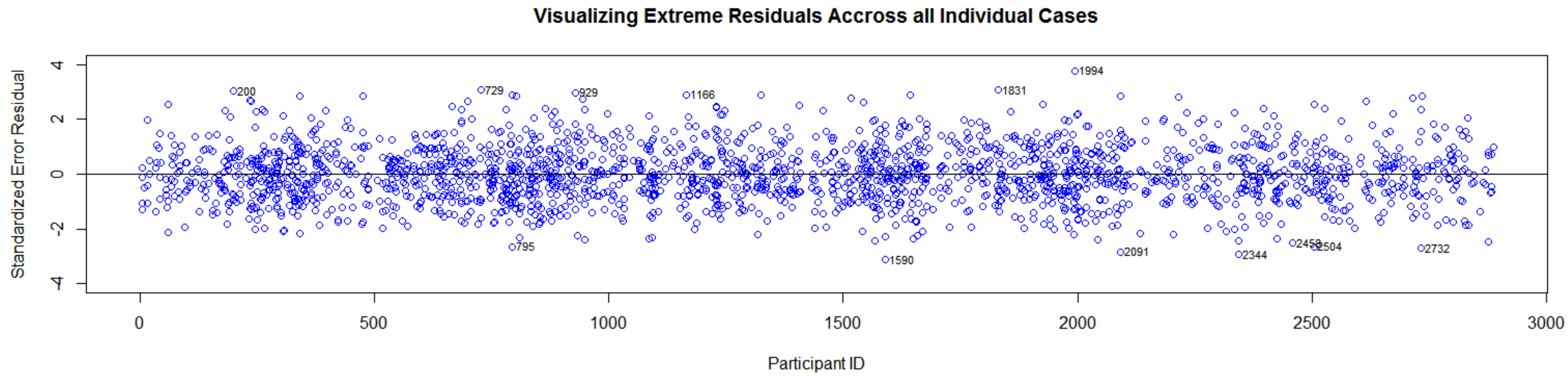

Figure 46
Visualizing extreme residuals in the MLM for the outcome of PSS.

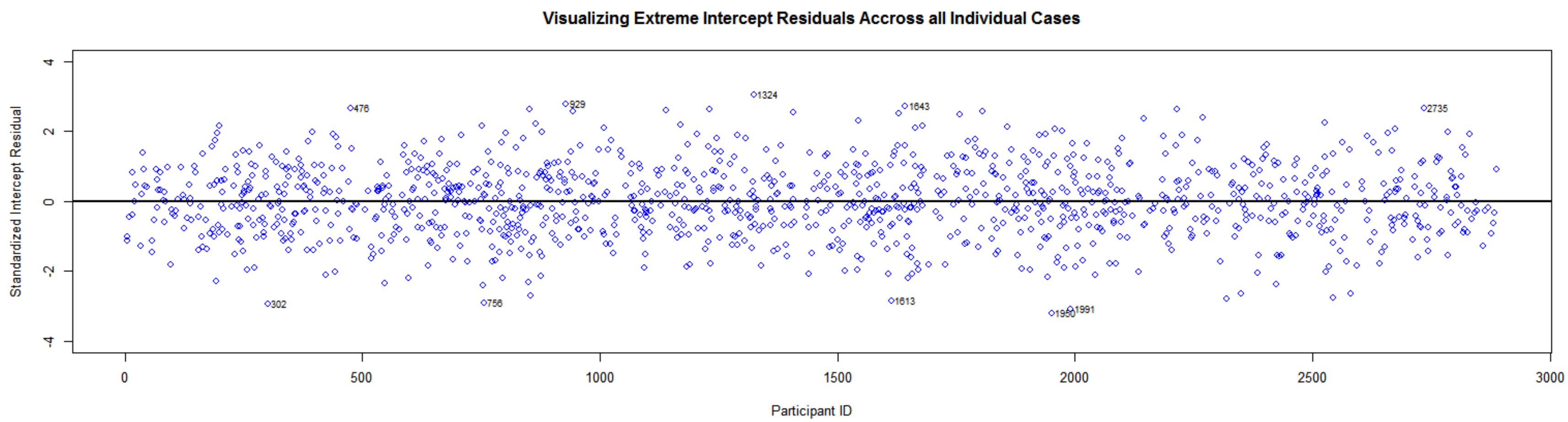

Figure 47
Visualizing extreme intercept residuals in the MLM for the outcome of PSS.

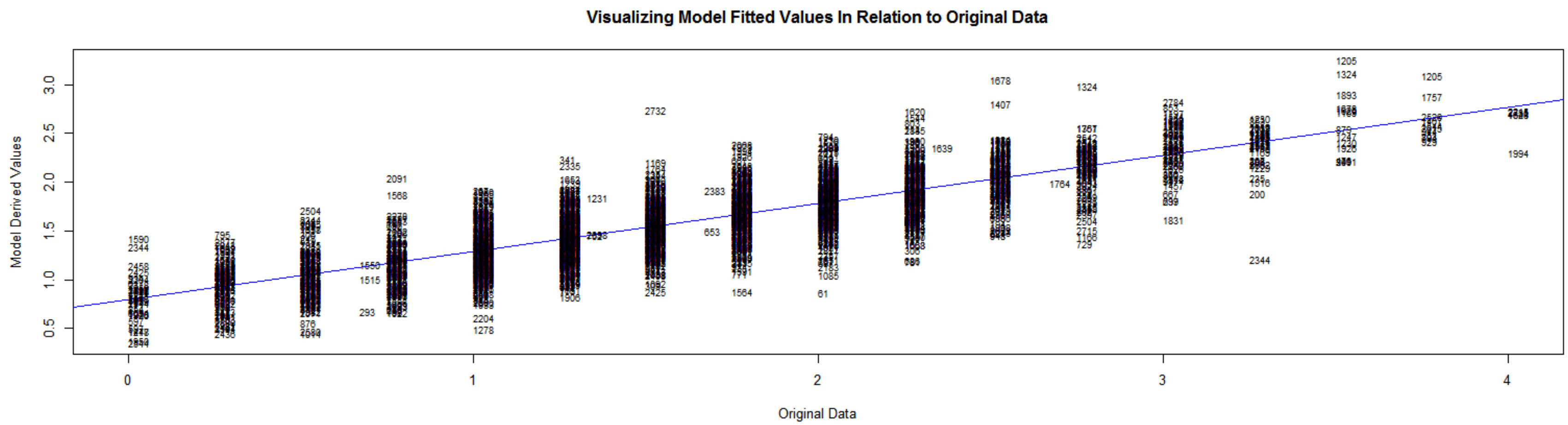

Figure 48
Visualizing model fitted values in the MLM for the outcome of PSS.

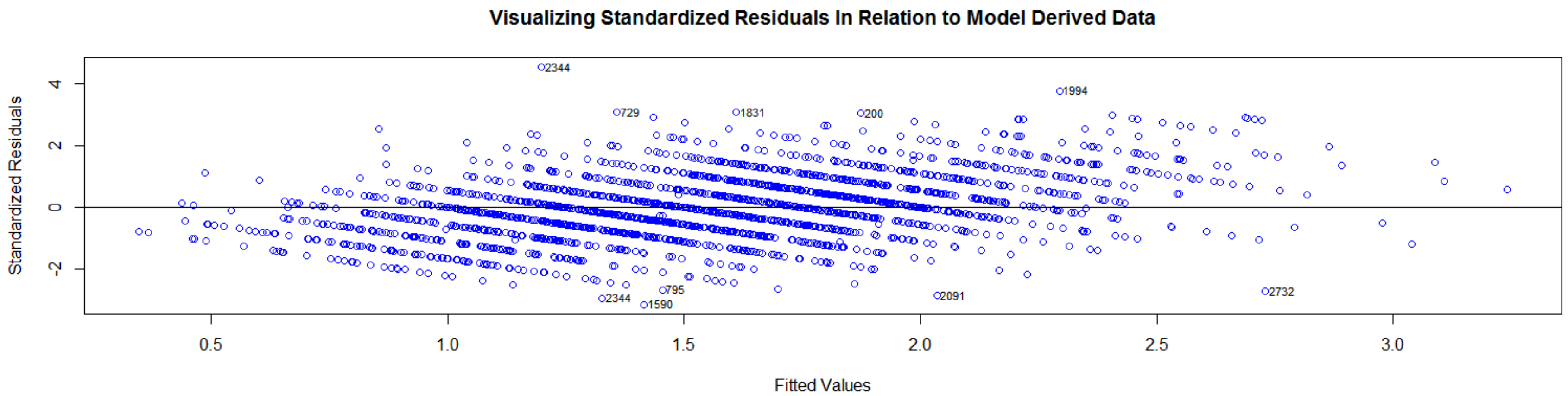

Figure 49
Visualizing standardized residuals in the MLM for the outcome of PSS.

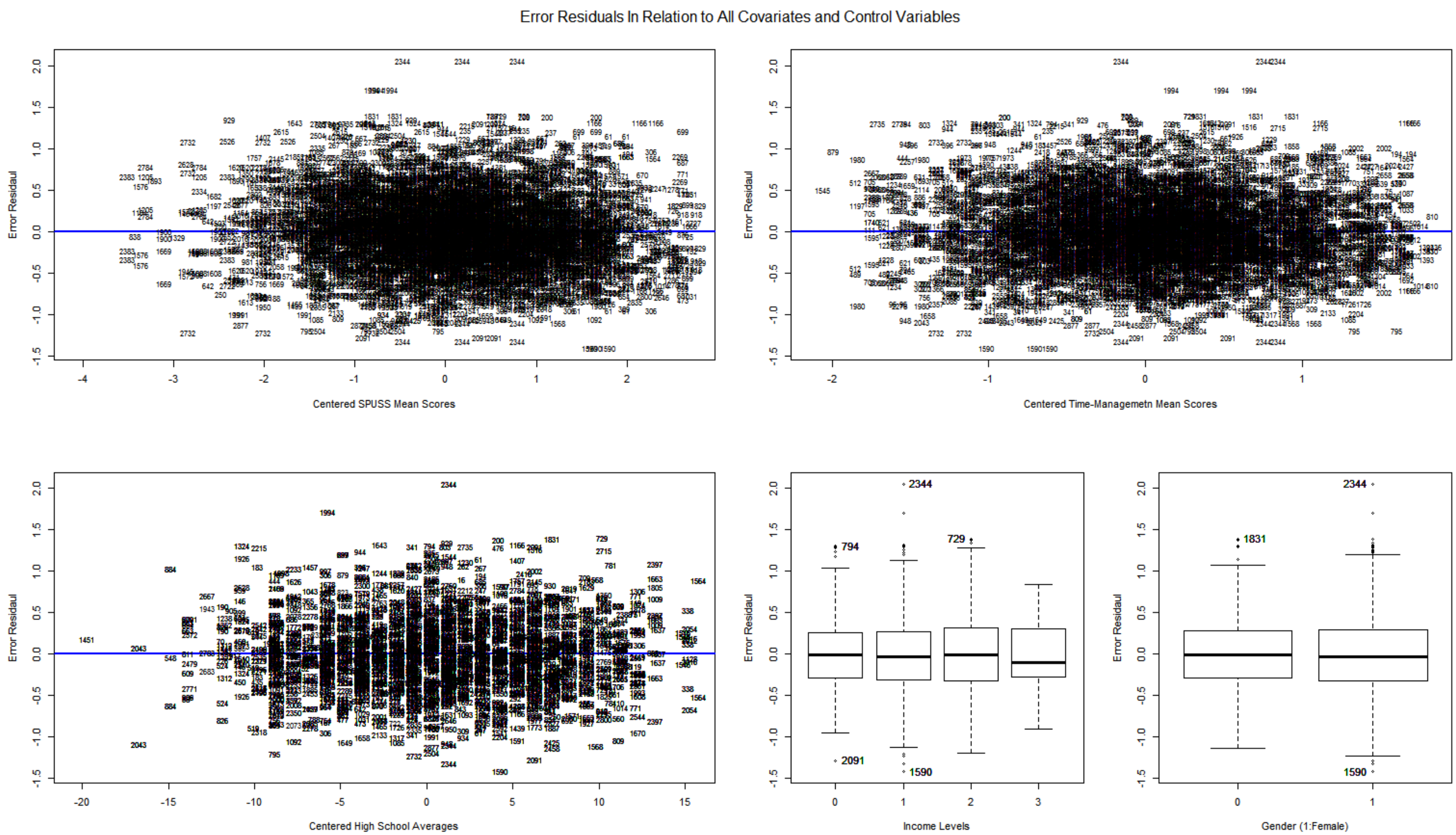

Figure 50
Error residuals in relation to all covariates in the MLM for the outcome of PSS.

Table 24
Homogeneity of Residual Variance in the MLM for the Outcome of PSS.

	df	F value	P
Levene Test Homogeneity of Residual Variance Across Genders	1, 5744	7.65	.006
Levene Test for Homogeneity of Residual Variance Across Income Levels	3, 5742	2.92	.032

Checking Assumptions of MLM – CES-D

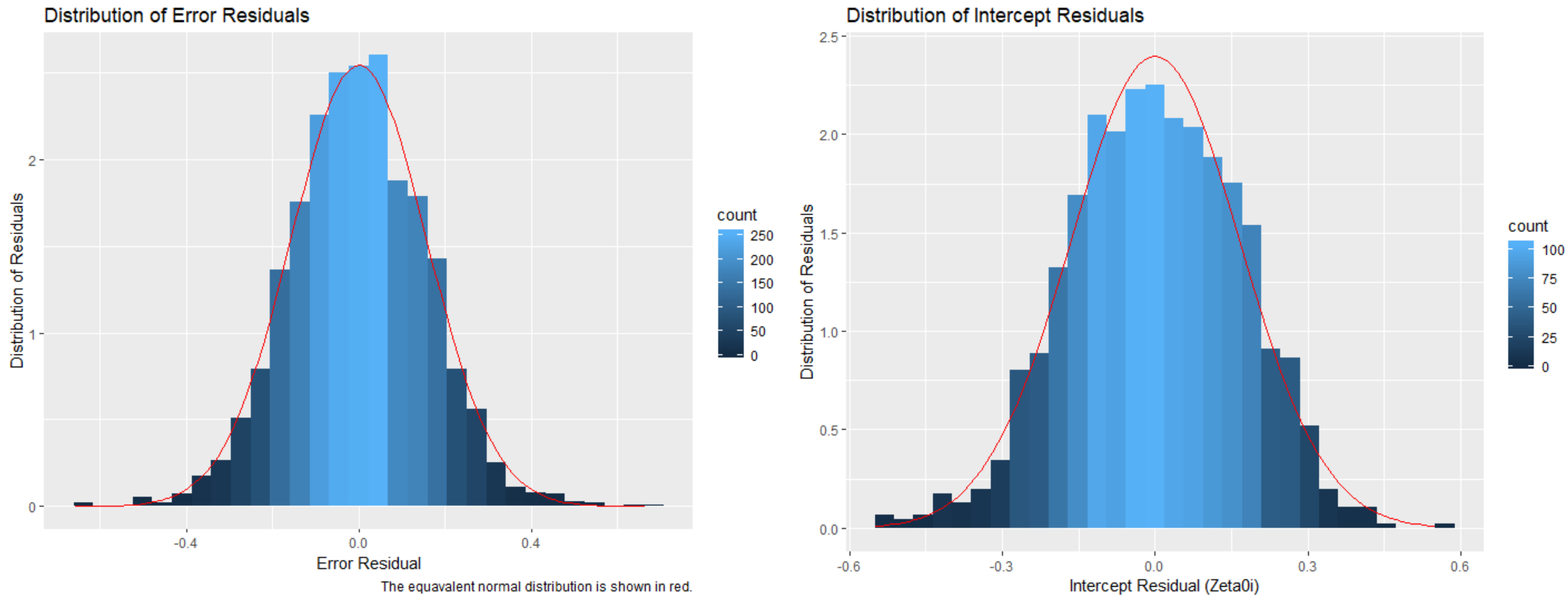

Figure 51
Distribution of error residuals in the MLM for the outcome of CES-D.

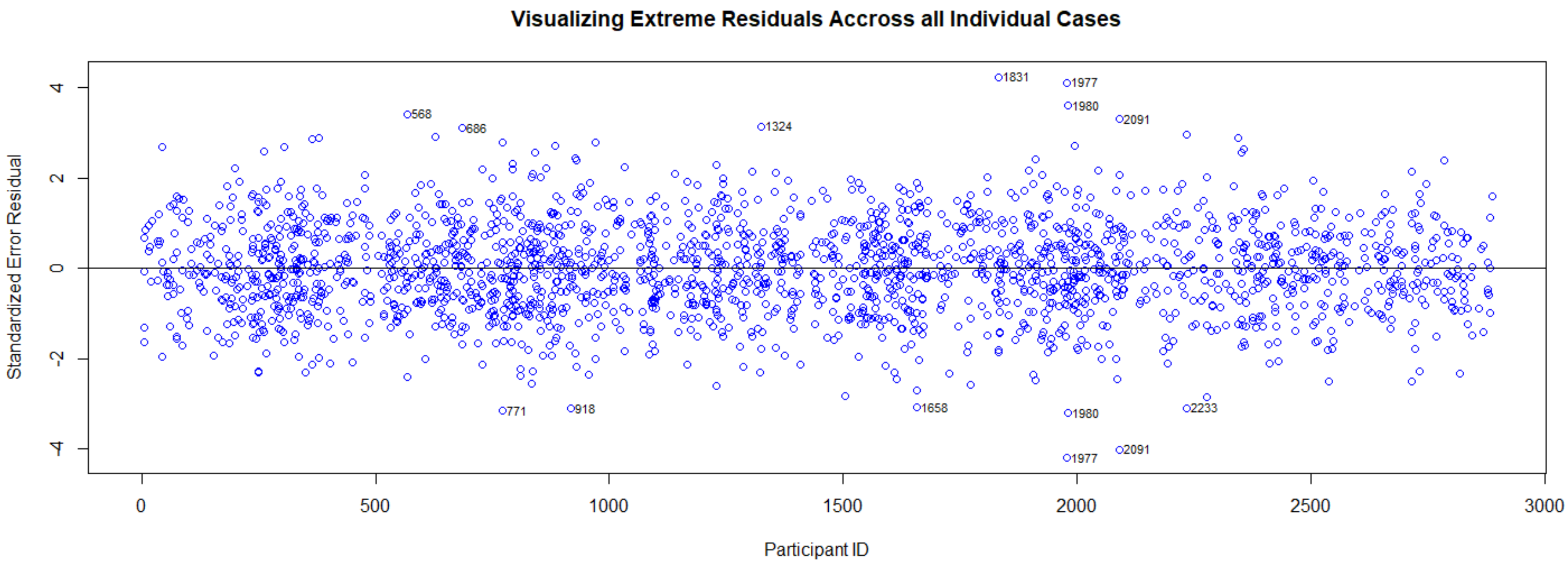

Figure 52
Visualizing extreme residuals in the MLM for the outcome of CES-D.

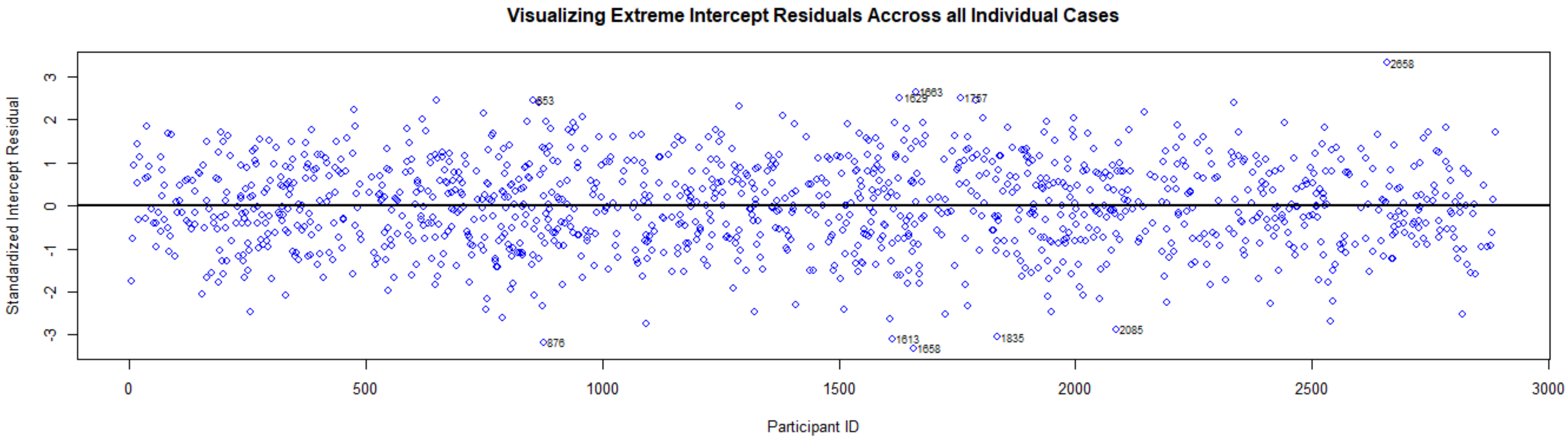

Figure 53
Visualizing extreme intercept residuals in the MLM for the outcome of CES-D.

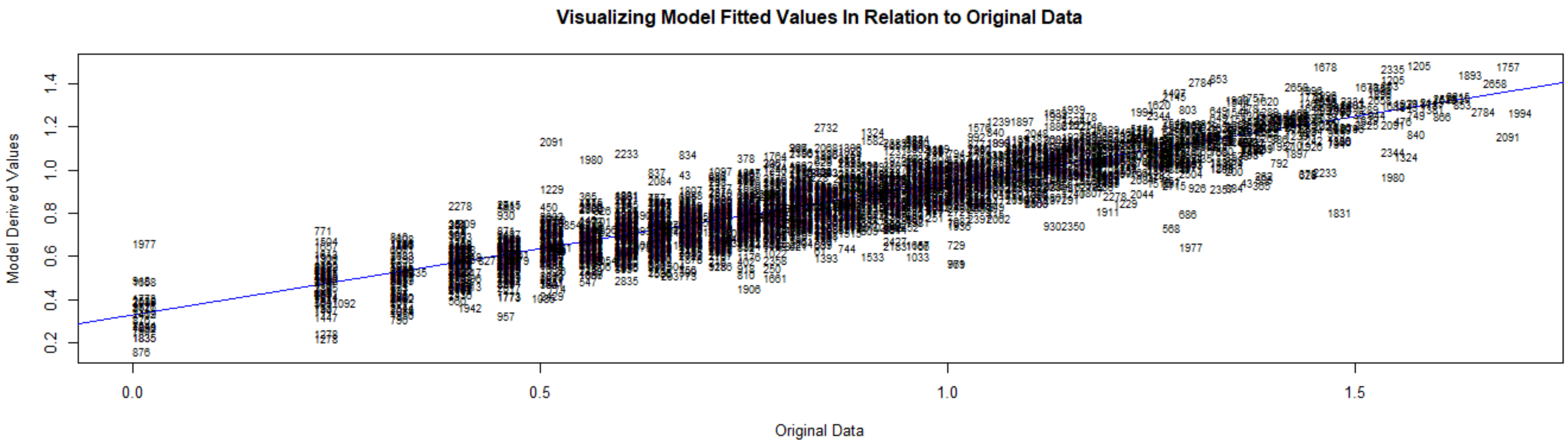

Figure 54
Visualizing model fitted values in the MLM for the outcome of CES-D.

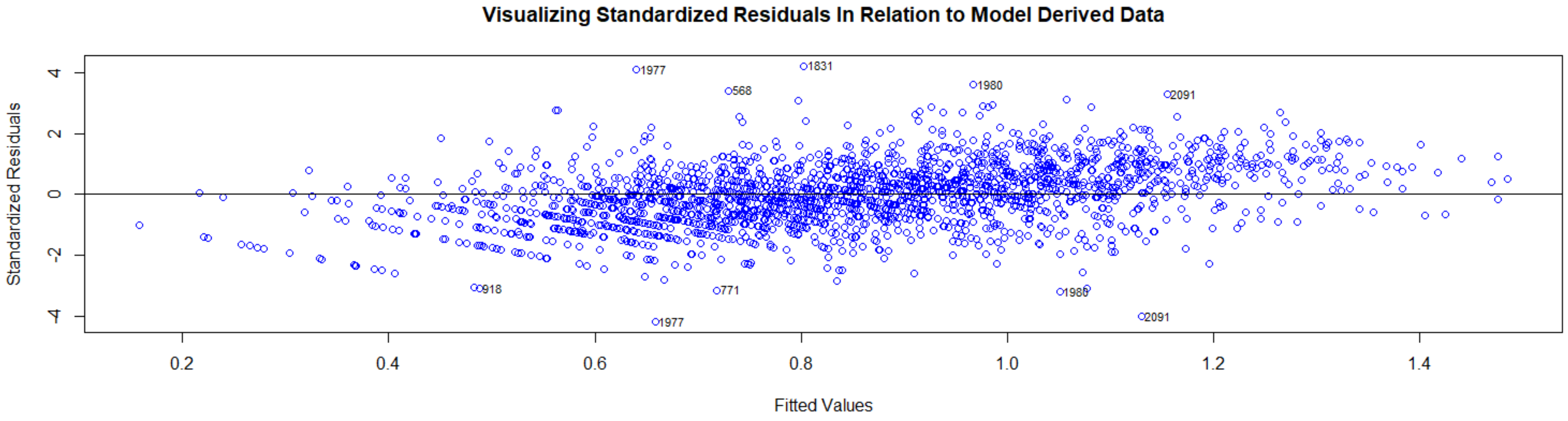

Figure 55
Visualizing Standardized residuals in the MLM for the outcome of CES-D.

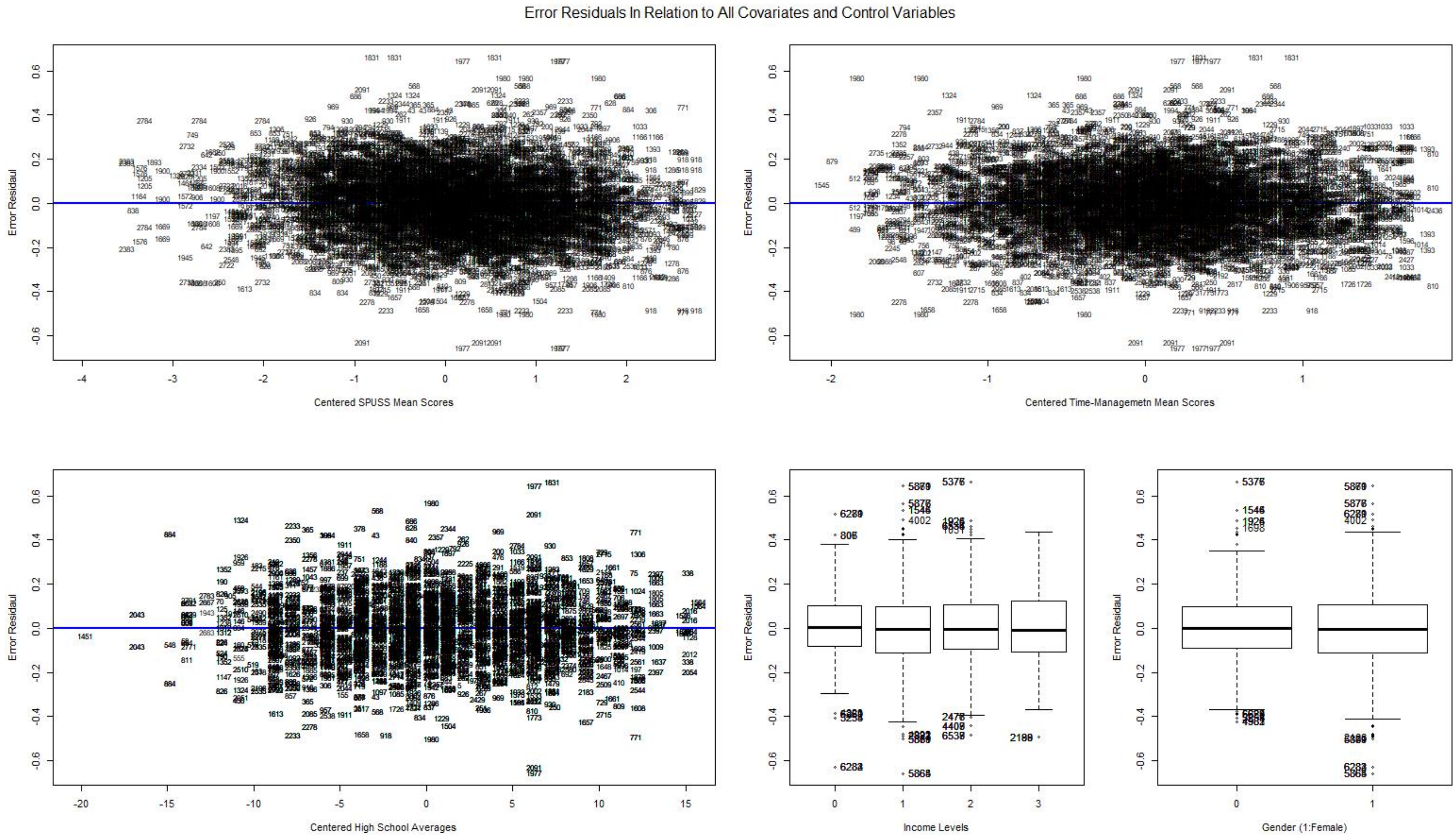

Figure 56
Error residuals in relation to all covariates in the MLM for the outcome of CES-D.

Table 25
Homogeneity of Residual Variance in the MLM for the Outcome of CES-D.

	df	F value	p
Levene Test Homogeneity of Residual Variance Across Genders	1, 5740	23.4	<.001
Levene Test for Homogeneity of Residual Variance Across Income Levels	3, 5738	1.48	.22

Checking Assumptions of MLM – TM

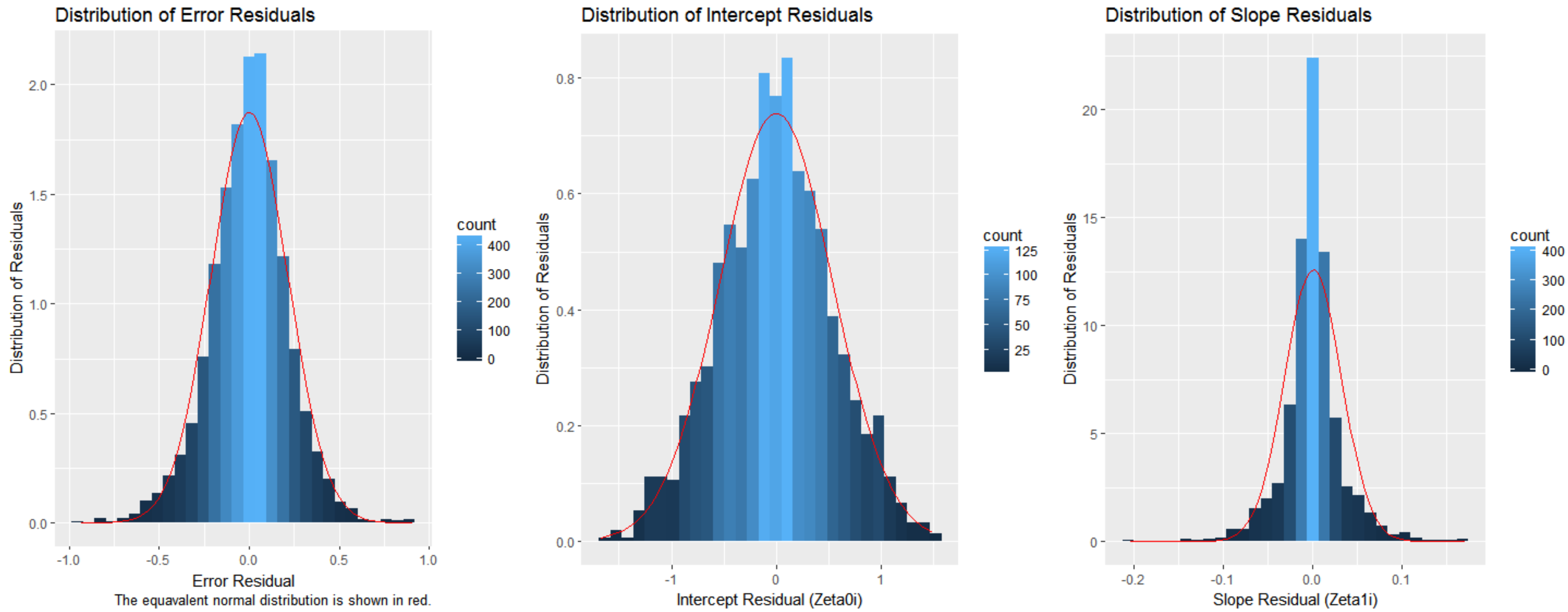

Figure 57
Distribution of error residuals in the MLM for the outcome of TM.

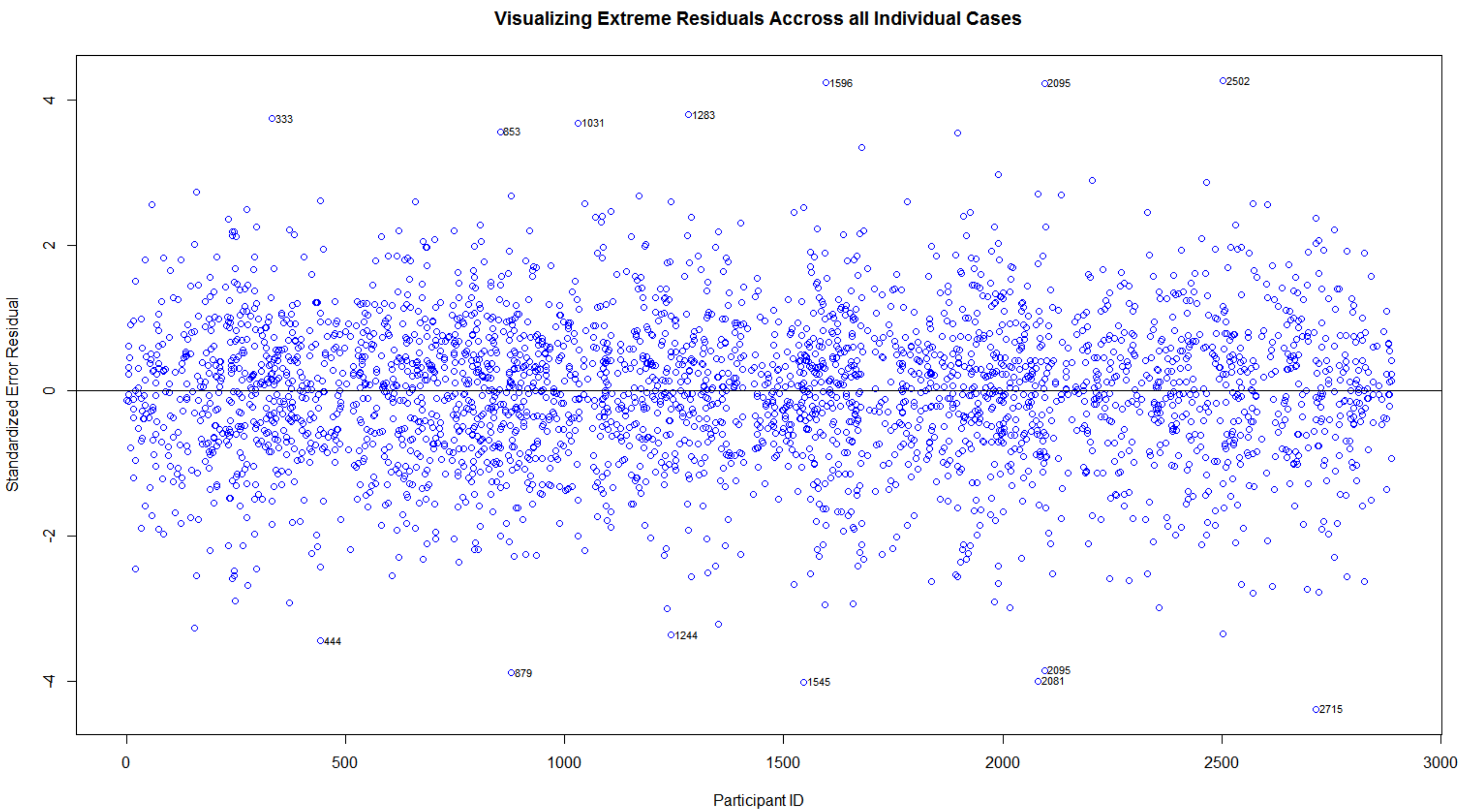

Figure 58
Visualizing extreme residuals in the MLM for the outcome of TM.

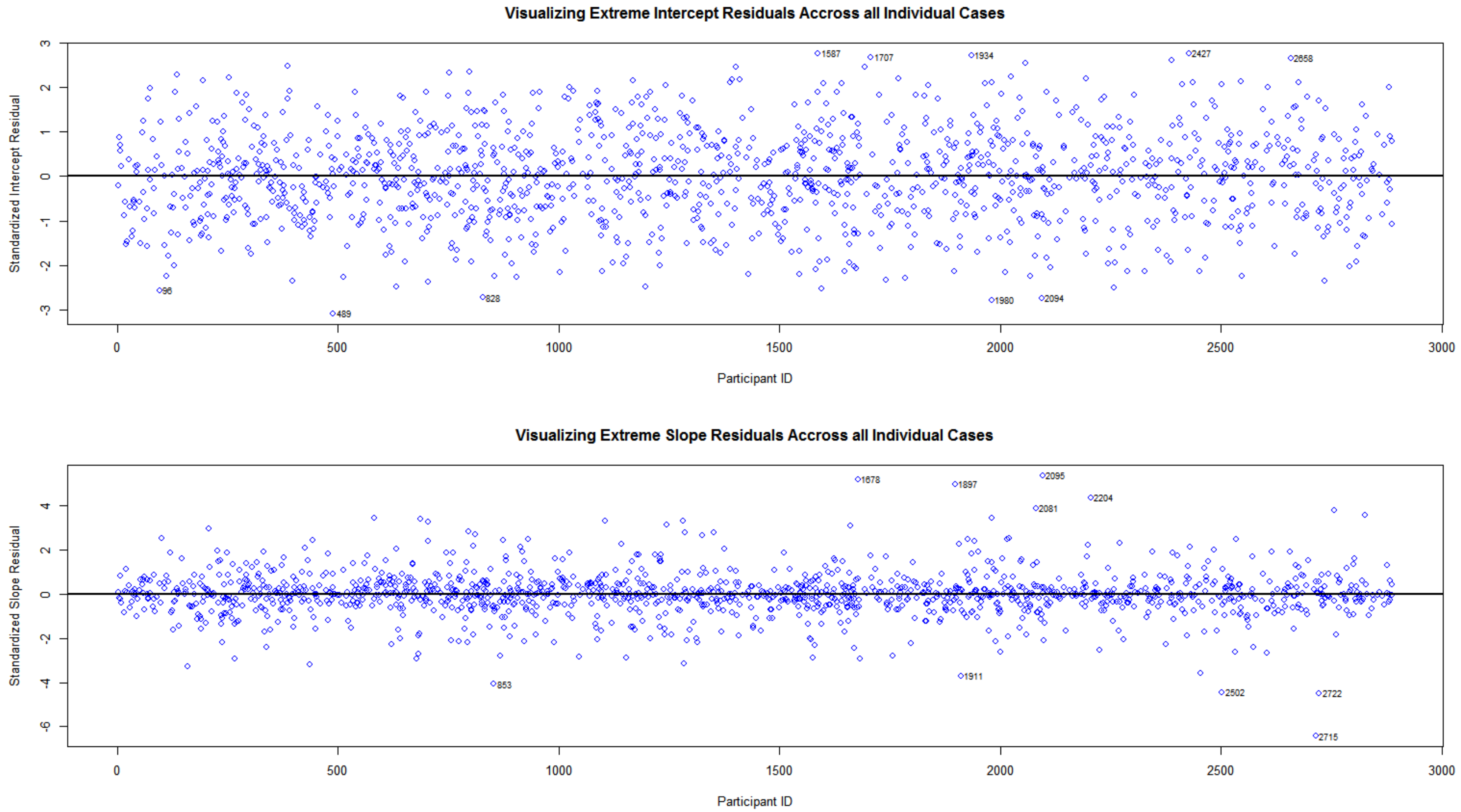

Figure 59
Visualizing extreme intercept and slope residuals in the MLM for the outcome of TM.

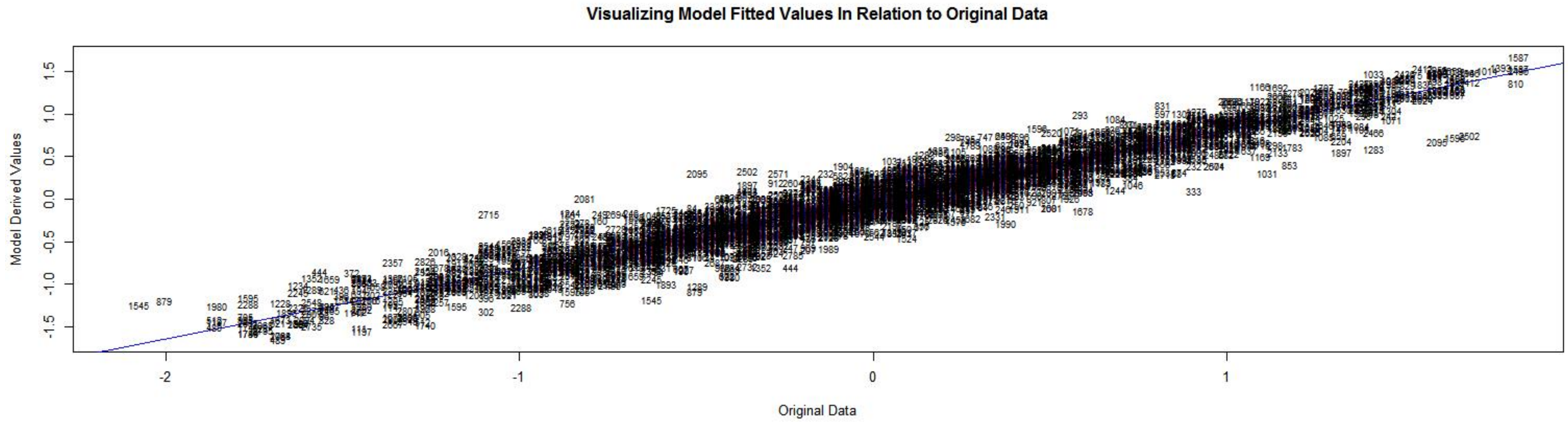

Figure 60
Visualizing model fitted values in the MLM for the outcome of TM.

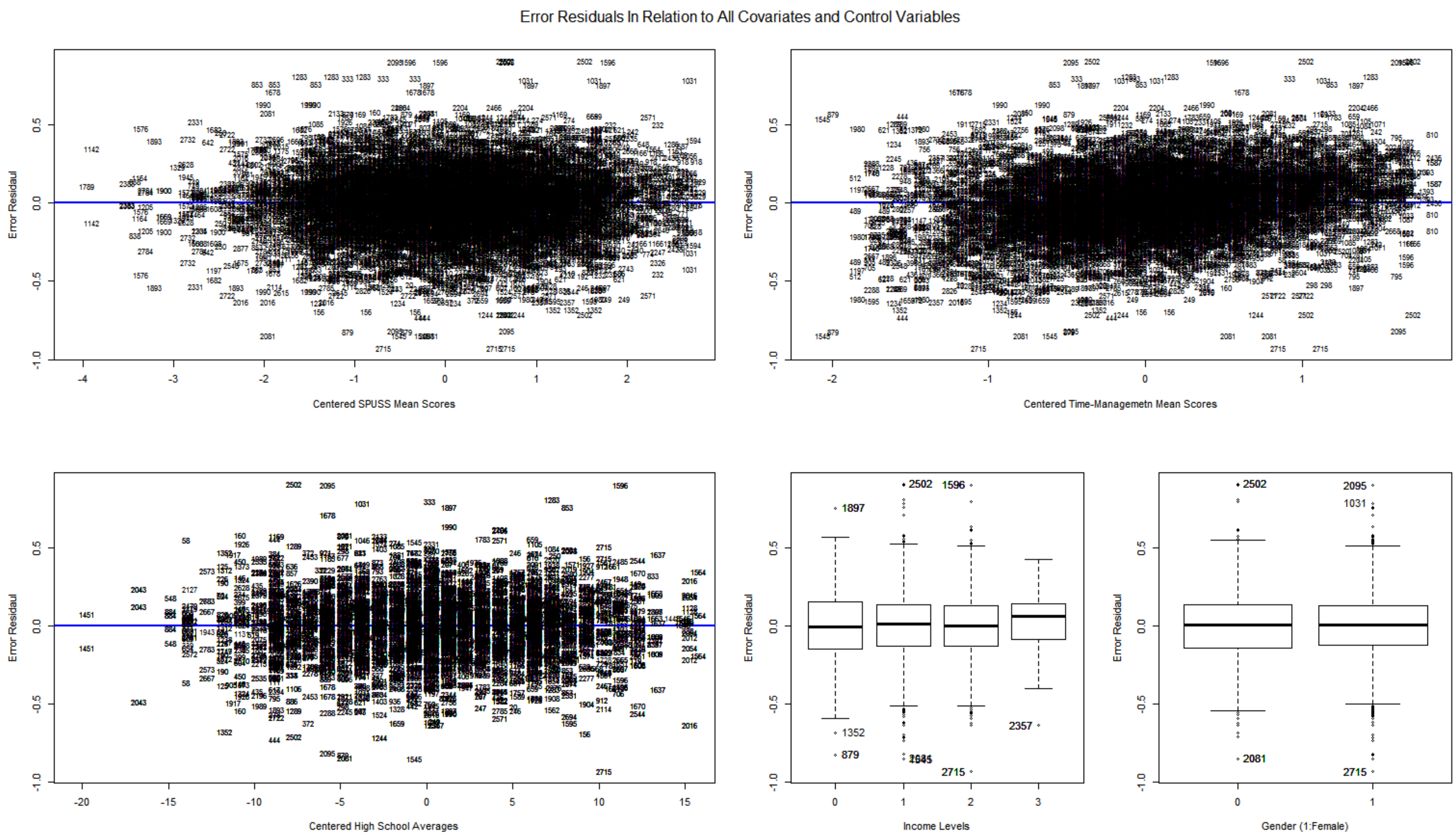

Figure 61
Error residuals in relation to all covariates in the MLM for the outcome of TM.

Table 26
Homogeneity of Residual Variance in the MLM for the Outcome of TM.

	df	F value	p
Levene Test Homogeneity of Residual Variance Across Genders	1, 7899	6.76	.009
Levene Test for Homogeneity of Residual Variance Across Income Levels	3, 7897	3.57	.013

Checking Assumptions of MLM – SPUSS

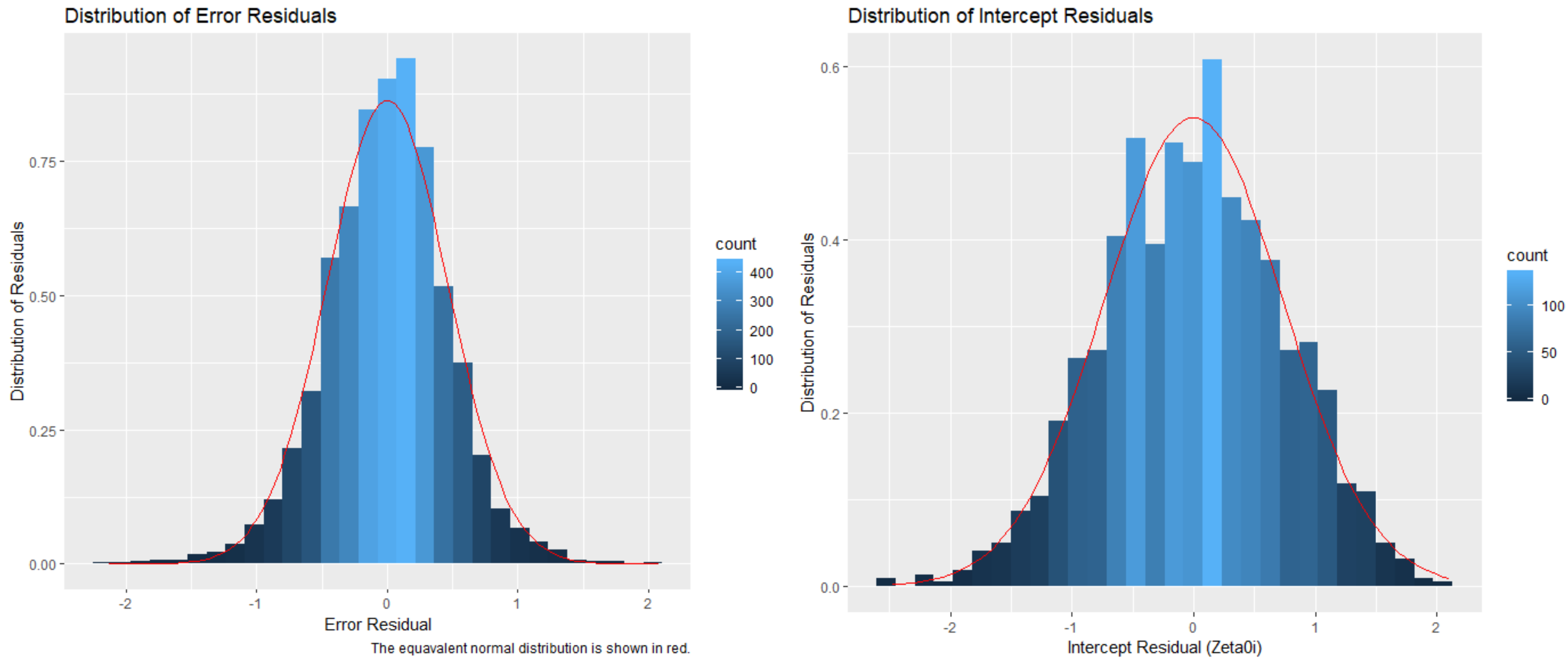

Figure 62
Distribution of error residuals in the MLM for the outcome of SPUSS.

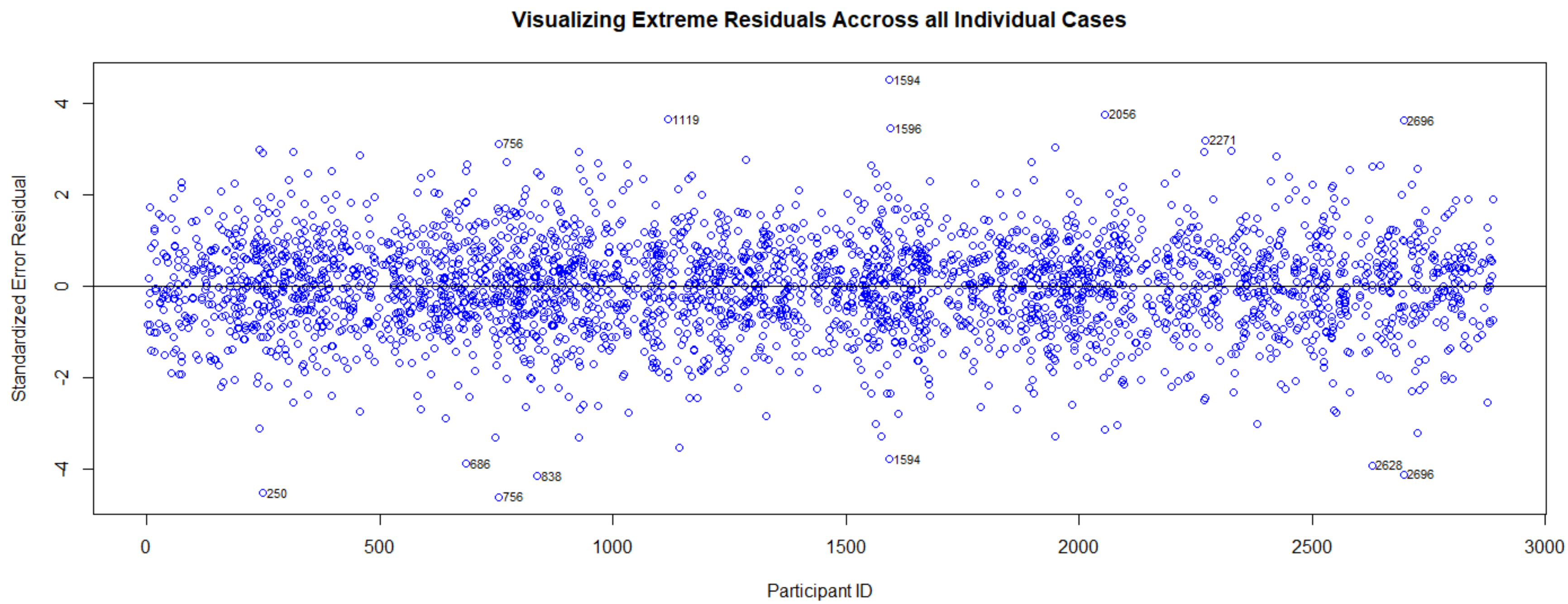

Figure 63
Visualizing extreme residuals in the MLM for the outcome of SPUSS.

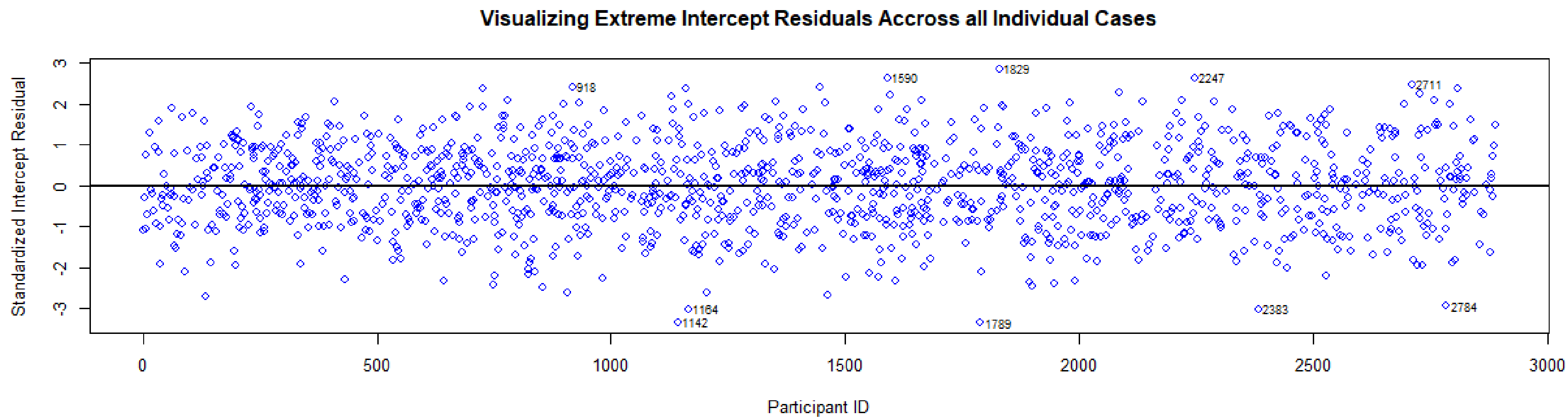

Figure 64
Visualizing extreme intercept residuals in the MLM for the outcome of SPUSS.

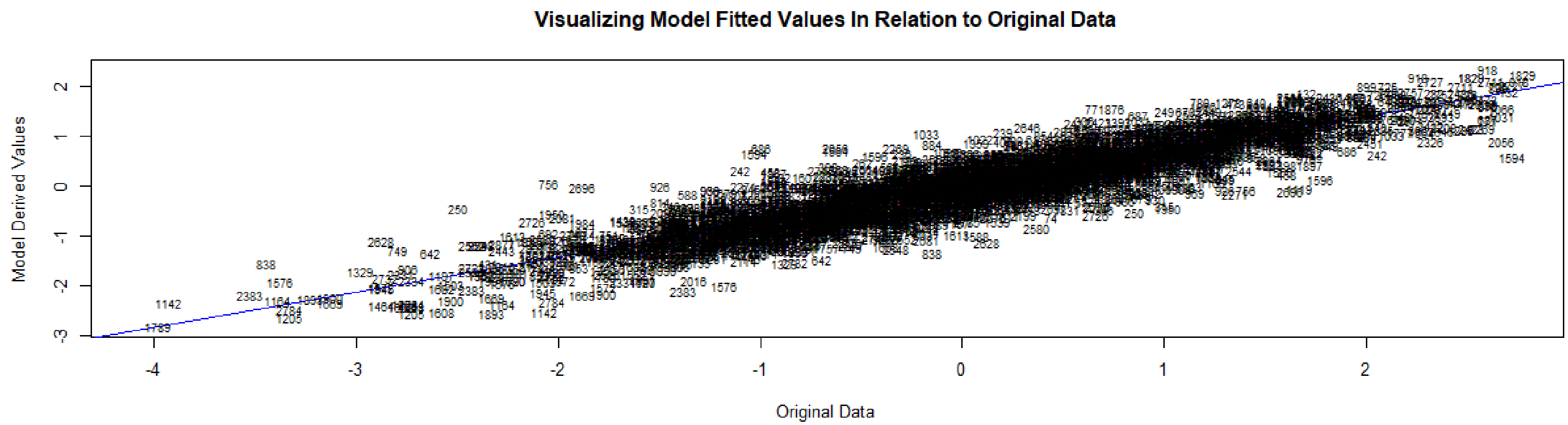

Figure 65
Visualizing model fitted values in the MLM for the outcome of SPUSS.

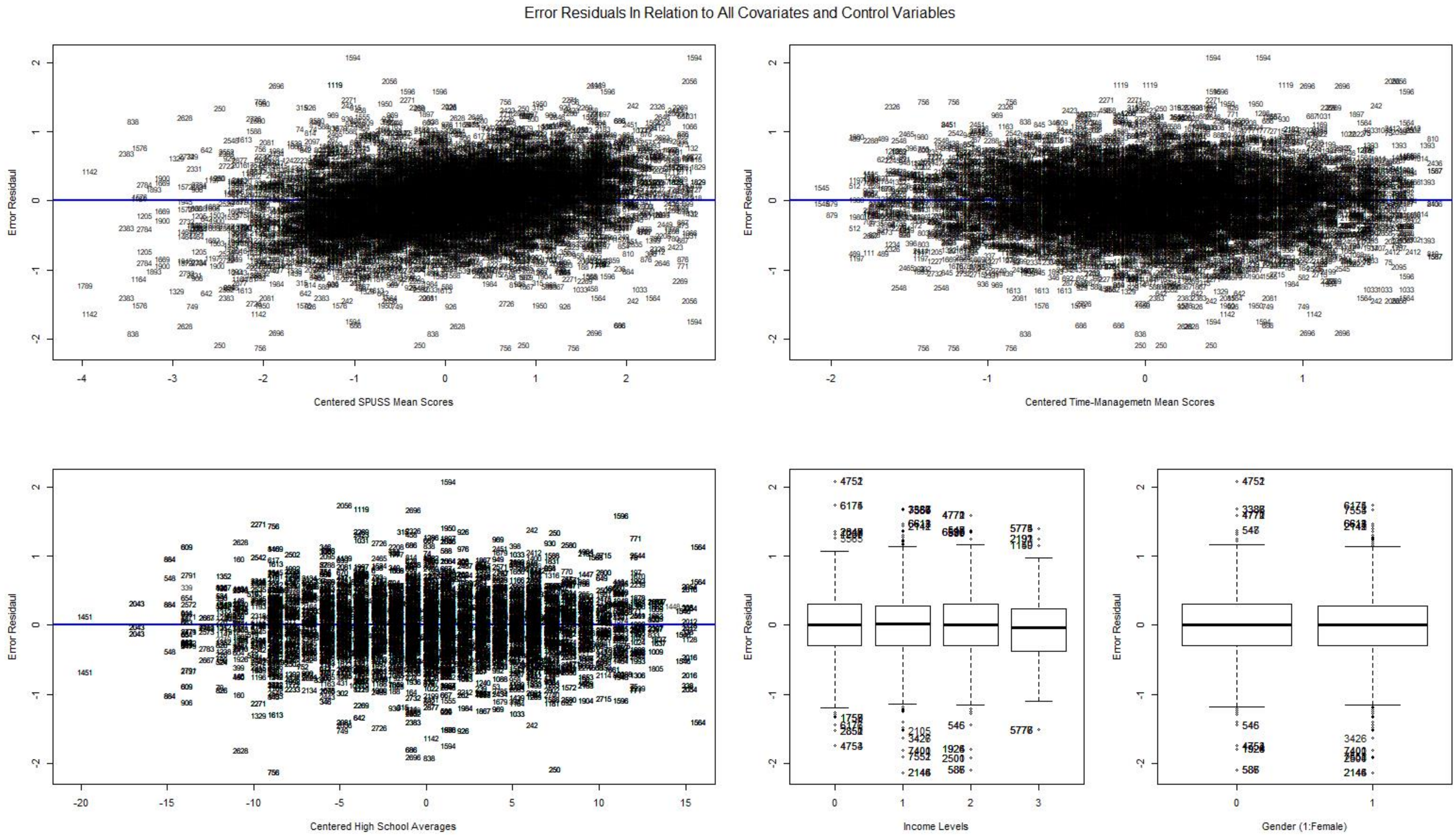

Figure 66
Error residuals in relation to all covariates in the MLM for the outcome of SPUSS.

Table 27
Homogeneity of Residual Variance in the MLM for the Outcome of SPUSS.

	df	F value	p
Levene Test Homogeneity of Residual Variance Across Genders	1, 7899	3.31	.069
Levene Test for Homogeneity of Residual Variance Across Income Levels	3, 7897	1.81	.143

Appendix B: Study Two Statistics

R Software Version and Packages

R software version 3.4.4 (2018-03-15) was used, and packages used for the analyses included:

```
attached base packages:
[1] grid      stats     graphics  grDevices utils     datasets  methods
[8] base

other attached packages:
 [1] bindrcpp_0.2.2  apaTables_2.0.5 scales_1.0.0    ggthemes_4.0.1
 [5] effsize_0.7.1   magrittr_1.5    dplyr_0.7.6     plyr_1.8.4
 [9] gridExtra_2.3   pander_0.6.3    stargazer_5.2.2 stringr_1.2.0
[13] ggplot2_3.0.0   reshape2_1.4.2  lattice_0.20-35 car_3.0-2
[17] carData_3.0-1   tidyr_0.6.3     xlsx_0.5.7      xlsxjars_0.6.1
[21] rJava_0.9-8

loaded via a namespace (and not attached):
 [1] Rcpp_0.12.18        assertthat_0.2.0    digest_0.6.16
 [4] psych_1.8.4         R6_2.2.2            cellranger_1.1.0
 [7] backports_1.1.2     acepack_1.4.1       rlang_0.2.2
[10] lazyeval_0.2.1      curl_3.2            readxl_1.1.0
[13] rstudioapi_0.7      data.table_1.11.4   rpart_4.1-13
[16] Matrix_1.2-12       checkmate_1.8.5     labeling_0.3
[19] splines_3.4.4       foreign_0.8-69      htmlwidgets_1.2
[22] munsell_0.5.0       broom_0.5.0         compiler_3.4.4
[25] pkgconfig_2.0.2     base64enc_0.1-3     mnormt_1.5-5
[28] htmltools_0.3.6     nnet_7.3-12         tidyselect_0.2.4
[31] htmlTable_1.12      tibble_1.3.3        Hmisc_4.1-1
[34] rio_0.5.10          withr_2.1.2         nlme_3.1-131.1
[37] gtable_0.2.0        zip_1.0.0           stringi_1.1.5
[40] latticeExtra_0.6-28 openxlsx_4.1.0      Formula_1.2-3
[43] RColorBrewer_1.1-2  tools_3.4.4         forcats_0.3.0
[46] glue_1.3.0          purrr_0.2.5         hms_0.4.2
[49] abind_1.4-5         parallel_3.4.4      survival_2.41-3
[52] yaml_2.2.0          colorspace_1.3-2    cluster_2.0.6
[55] MBESS_4.4.3         knitr_1.20          bindr_0.1.1
```

Distribution of ISD values for Study Two

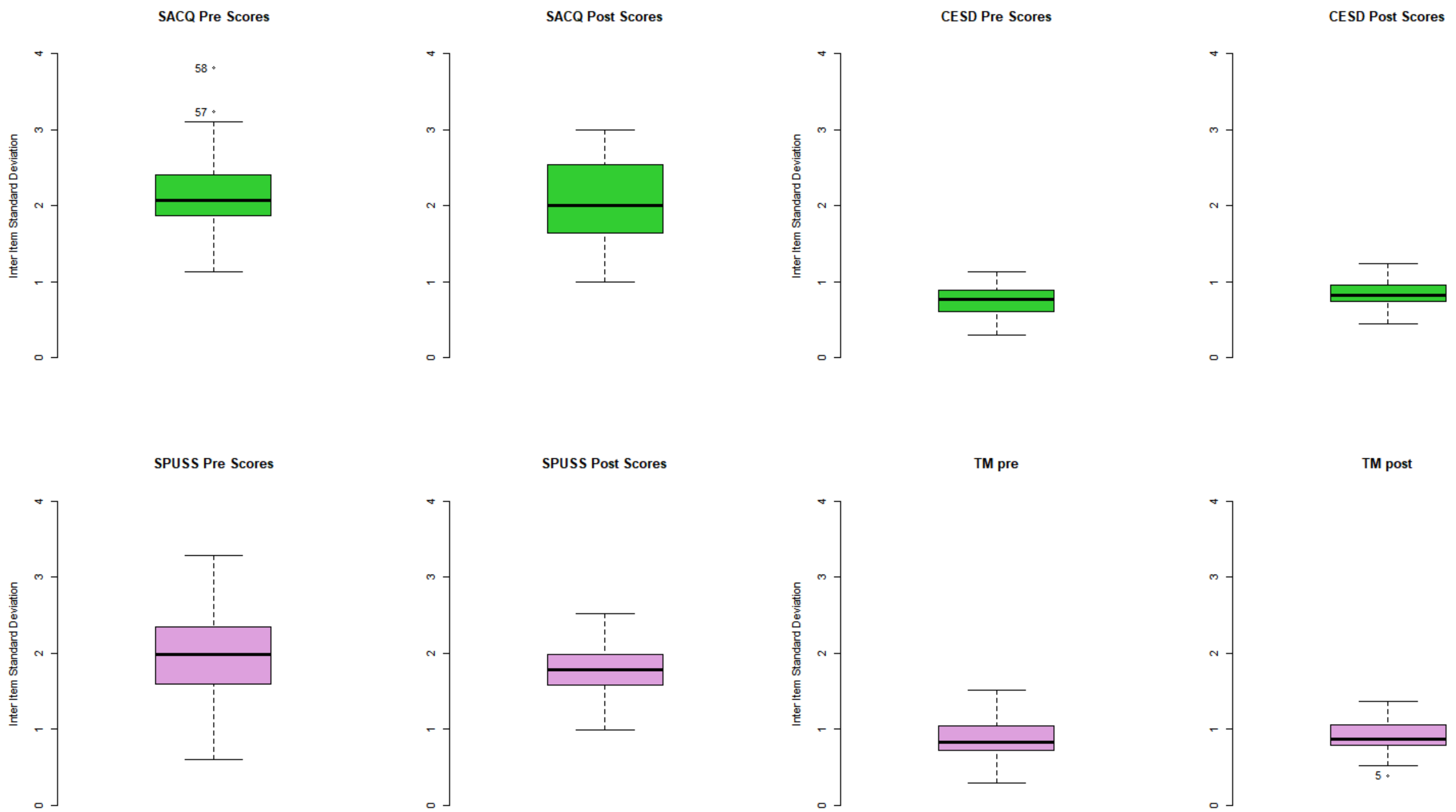

Figure 67: Distribution of ISD values in Study 2.

Regression on Course Grades Assumption Verification

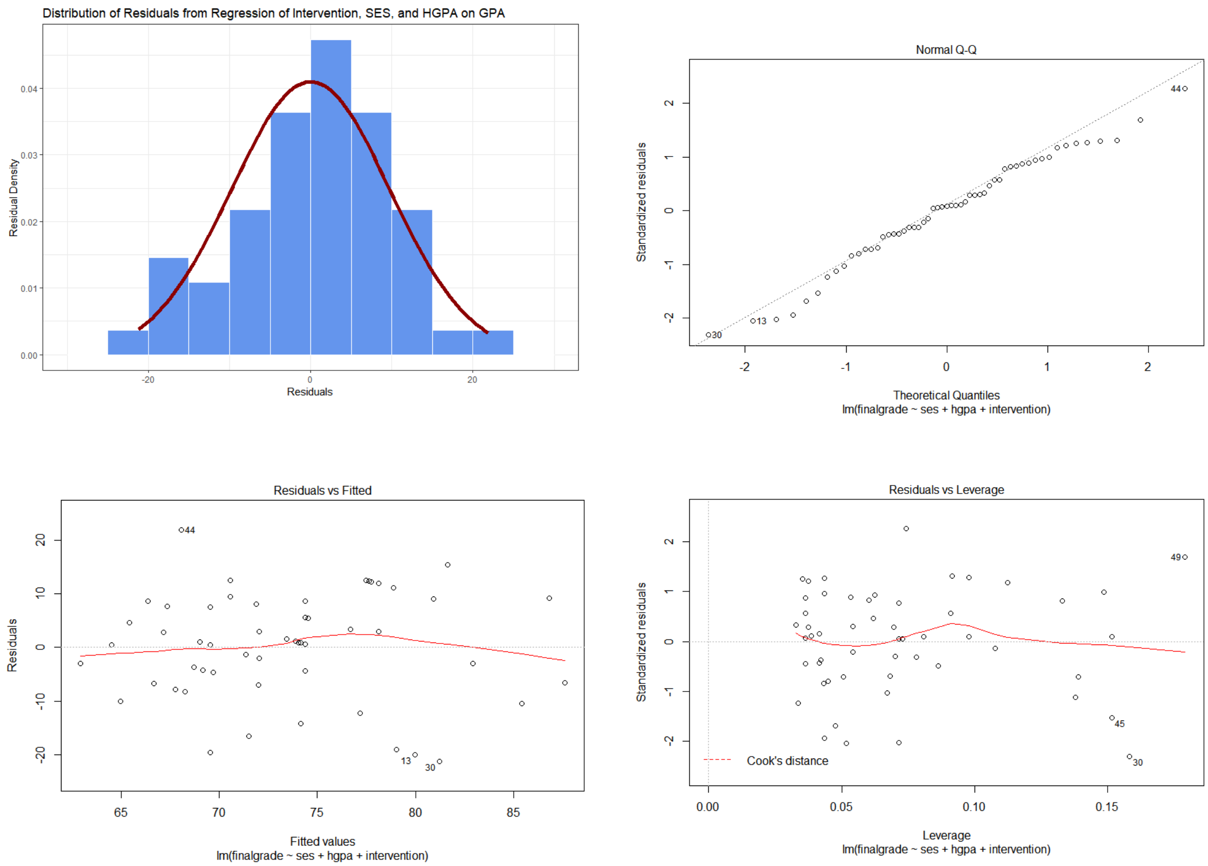

Figure 68: Regression on course grades assumption verification

Appendix C: Statistical Analysis Software Code and Output

```
#####          STUDY 1 – T2U Longitudinal Models    ######

library (tidyr)
library (car)
## Loading required package: carData
library (lattice)
library (reshape2)
##
## Attaching package: 'reshape2'
## The following object is masked from 'package:tidyr':
##
##     smiths
library (ggplot2)
library (nlme)
library (piecewiseSEM)
##
##   This is piecewiseSEM version 2.0.2
##
##   If you have used the package before, it is strongly recommended you read Section 3 of the vignette('piecewiseSEM') t
o familiarize yourself with the new syntax
##
##   Questions or bugs can be addressed to <EMAIL>
library (stringr)
library (predictmeans)
## Loading required package: lme4
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
## The following object is masked from 'package:tidyr':
##
##     expand
##
## Attaching package: 'lme4'
## The following object is masked from 'package:nlme':
##
##     lmList
## Loading required package: parallel
library (stargazer)
##
## Please cite as:
##  Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.
##  R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
library (pander)
library (grid)
library (gridExtra)
library (plyr)
library (magrittr)
##
## Attaching package: 'magrittr'
## The following object is masked from 'package:tidyr':
##
##     extract
library (DescTools)
## Warning: package 'DescTools' was built under R version 3.5.3
##
## Attaching package: 'DescTools'
## The following object is masked from 'package:car':
##
##     Recode
library (effsize)
dat.inclusive <- read.csv("T2U.csv",  header = TRUE)
names(dat.inclusive)[1] <- "idold"
dat.inclusive$id <- seq.int(nrow(dat.inclusive))

#exclusions:
dat <- dat.inclusive[dat.inclusive$exclusion==1,]
dat <- dat[!is.na(dat$ahs_avg),]
dat <- dat[!is.na(dat$agender),]
dat <- dat[!is.na(dat$income),]

#removing columns
dat <- dat[,-which(colnames(dat)=="yesT2")]
dat <- dat[,-which(colnames(dat)=="yesT3")]
dat <- dat[,-which(colnames(dat)=="yesT4")]
dat <- dat[,-which(colnames(dat)=="yesT5")]
```

```r
dat <- dat[,-which(colnames(dat)=="idold")]


#transform to undifferentiated long format with Reshape
dat.messy<-melt(data=dat,
              id.vars=c("id","sample","univ","exclusion","agender","age","ahs_avg",
                        "alang","acntry","income","momedu","dadedu"),
              variable.name="var",value.name="value")

#seperating Time and Measure Columns
dat.sep <- separate(dat.messy,
                    var, into = c("time", "measure"), sep = "\\_")

#recoding Time to numeric based on semesters
dat.sep$time<- car::recode(dat.sep$time,"'T2'=0;
                     'T3'=1; 'T4'=2;'T5'=3",as.numeric=TRUE)
dat.sep <- dat.sep [order(dat.sep$id),]

#Seperating the Variable Columns
dat.long = dcast(dat.sep, id + sample + univ + exclusion + agender + age +
                   ahs_avg + alang + acntry + income + momedu +
                   dadedu + time  ~ measure, value.var = "value" )
dat.long <- dat.long [order(dat.long$id),]

#excluding NAs in covariates
dat.long <- dat.long[!is.na(dat.long$SPUSS.mean),]

#Setting up Labels
dat.long$sample <- factor(dat.long$sample,levels = c(1,2),labels = c("2004 Cohort",
                                                                      "2005 Cohort"))
dat.long$univ <- factor(dat.long$univ,levels = c(1,2,3,4,5,6),
                        labels = c("WLU","Guelph","UTE","UTG","York", "MUN"))

## excel table copy function for transfering results:
exceltable <- function(x,row.names=TRUE,col.names=TRUE,...) {
  write.table(x,"clipboard",sep="	",row.names=row.names,col.names=col.names,...)
}
# Setting Up lagged design by moving the time of all outcomes forward by 1
#seperating Time and Measure Columns
dat.sep.lag <- separate(dat.messy,
                        var, into = c("time", "measure"), sep = "\\_")

#recoding time to numeric

dat.sep.lag$time<-car::recode(dat.sep.lag$time,"'T2'=2;
                         'T3'=3; 'T4'=4;'T5'=5",as.numeric=TRUE)

#moving non-covariates back by 1
for (row in seq_len(nrow(dat.sep.lag))){
  if (dat.sep.lag$measure[row]!= "SPUSS.mean" & dat.sep.lag$measure[row]!= "TM.mean" &
      dat.sep.lag$measure[row]!= "SPUSS.sdi" & dat.sep.lag$measure[row]!= "TM.sdi")
  {
    dat.sep.lag$time[row] = dat.sep.lag$time[row] -1
  }
}

#recoding Time to semesters and removing out of bounds data points
dat.sep.lag$time<-car::recode(dat.sep.lag$time,"'1'=99;'2'=0;
                         '3'=1; '4'= 2;'5'=99",as.numeric=TRUE)
dat.sep.lag <- dat.sep.lag[!dat.sep.lag$time==99,]

#Seperating the Variable Columns
lagdat = dcast(dat.sep.lag, id + sample + univ + exclusion + agender + age +
                 ahs_avg + alang + acntry + income + momedu +
                 dadedu + time  ~ measure, value.var = "value" )
lagdat <- lagdat [order(lagdat$id),]

#excluding NAs in covariates
lagdat <- lagdat[!is.na(lagdat$SPUSS.mean),]
lagdat <- lagdat[!is.na(lagdat$TM.mean),]

#Setting up Labels
lagdat$sample <- factor(lagdat$sample,levels = c(1,2),labels = c("2004 Cohort", "2005 Cohort"))
lagdat$univ <- factor(lagdat$univ,levels = c(1,2,3,4,5,6),
                      labels = c("WLU","Guelph","UTE","UTG","York", "MUN"))
```

```r
lagdat$income<-car::recode(lagdat$income,"'1'=0;'2'=1; '3'=2;'4'=3",as.numeric=TRUE)
lagdat$incomef <- factor(lagdat$income,levels = c(0,1,2,3),
                         labels = c("Below Average","Average"," Above Average","Well Above Average"))
#recoding gender
lagdat$agender<-car::recode(lagdat$agender,"'1'=0;'2'=1",as.numeric=TRUE)
lagdat$agenderf <- factor(lagdat$agender,levels = c(0,1),labels = c("Male", "Female"))


#using old optimizer
ctrl <- lmeControl(opt='optim'); #did not converge trying the old optimizer
lagdat$semester <- car::recode(lagdat$time,"'0'=0;'1'=1; '2'=4",as.numeric=TRUE)
#Used for exploring outliers from SDI or from Assumptions function after MLM
#Lets take a moment to appreciate the beauty of functionalizing routine operations :)

outlier <-function (dataset, idnumber) {

p <- ggplot(data = dataset[dataset$id == idnumber,], aes(x = time, y = SACQ.mean, group = id))+
  geom_line( aes(col=univ),size = 1.2, alpha = .5) +
  xlab("Academic Year") + ylab("Mean SACQ Scores") +
  theme(plot.title = element_text(hjust = 0.5)) + labs(colour = "University:") +
  ylim(min(dataset$SACQ.mean, na.rm = TRUE),max(dataset$SACQ.mean, na.rm = TRUE))+
  ggtitle(paste("SACQ Over Time", " - Participant ID : ", idnumber))

p2 <- ggplot(data = dataset[dataset$id == idnumber,], aes(x = time, y = CESD.mean, group = id))+
  geom_line( aes(col=agenderf),size = 1.2, alpha = .5) +
  xlab("Academic Year") + ylab("CESD") + labs(colour = "Gender:") +
  theme(plot.title = element_text(hjust = 0.5)) +
  ylim(min(dataset$CESD.mean, na.rm = TRUE),max(dataset$CESD.mean, na.rm = TRUE))+
  ggtitle("CESD  Over Time")

p3 <- ggplot(data = dataset[dataset$id == idnumber,], aes(x = time, y = PSS.mean, group = id))+
  geom_line( aes(col=sample),size = 1.2, alpha = .5) +
  xlab("Academic Year") + ylab("PSS") +
  theme(plot.title = element_text(hjust = 0.5)) +labs(colour = "Sample Cohort:") +
  ylim(min(dataset$PSS.mean, na.rm = TRUE),max(dataset$PSS.mean, na.rm = TRUE))+
  ggtitle("PSS  Over Time")

p4 <- ggplot(data = dataset[dataset$id == idnumber,], aes(x = time, y = TM.mean, group = id))+
  geom_line(aes(col=factor(ahs_avg)), size = 1.2) +
  xlab("Academic Year") + ylab("TM") +
  theme(plot.title = element_text(hjust = 0.5)) + labs(colour = "Highschool \n Average:") +
  ylim(min(dataset$TM.mean, na.rm = TRUE),max(dataset$TM.mean, na.rm = TRUE))+
  ggtitle("TM  Over Time")

p5 <- ggplot(data = dataset[dataset$id == idnumber,], aes(x = time, y = SPUSS.mean, group = id))+
  geom_line(aes(col=factor(age)),size = 1.2) +
  xlab("Academic Year") + ylab("SPUSS") +
  theme(plot.title = element_text(hjust = 0.5)) + labs(colour = "Age at Start:") +
  ylim(min(dataset$SPUSS.mean, na.rm = TRUE),max(dataset$SPUSS.mean, na.rm = TRUE))+
  ggtitle("SPUSS  Over Time")

grid.arrange(p,p2,p3,p4,p5)

}
outliercount <- 3
par(mfrow=c(1,4))
sdi.spuss<-Boxplot(lagdat$SPUSS.sdi[lagdat$SPUSS.sdi!=0],
                   lagdat$time[lagdat$SPUSS.sdi!=0],
                   id.n = outliercount, labels = lagdat$id[lagdat$SPUSS.sdi!=0],
                   col = "plum", lwd = 2.5,bty="n", xlab = "SPUSS SDI", ylab = "Inter Item Standard Deviation")
box(lwd=3)

sdi.tm<-Boxplot(lagdat$TM.sdi[lagdat$TM.sdi!=0],
                lagdat$time[lagdat$TM.sdi!=0],
                id.n = outliercount, labels = lagdat$id[lagdat$TM.sdi!=0],
                col = "plum", lwd = 2.5,bty="n", xlab = "Time-Management SDI", ylab = "")
box(lwd=3)


sdi.sacq<-Boxplot(lagdat$SACQ.sdi[lagdat$SACQ.sdi!=0],
                  lagdat$time[lagdat$SACQ.sdi!=0],
                  id.n = outliercount, labels = lagdat$id[lagdat$SACQ.sdi!=0],
                  col = "limegreen", lwd = 2.5,bty="n", xlab = "SACQ SDI",ylab = "")
box(lwd=3)

sdi.cesd<-Boxplot(lagdat$CESD.sdi[lagdat$CESD.sdi!=0],
                  lagdat$time[lagdat$CESD.sdi!=0],
```

```
                  id.n = outliercount, labels = lagdat$id[lagdat$CESD.sdi!=0],
                  col = "limegreen", lwd = 2.5,bty="n", xlab = "CESD SDI",ylab = "")
box(lwd=3)
mtext("The Inter-item Standard Deviation of Key Measures for Individuals Accross Time (Excluding Zeroes)" ,
      outer = TRUE, cex = 1.5, side = 3, line = -2)

sdi.all <- list (sdi.spuss,sdi.tm, sdi.sacq, sdi.cesd)
print(sdi.all)
## [[1]]
##  [1] "573"  "968"  "1200" "2444" "2468" "555"  "813"  "954"  "1378" "1859"
## [11] "2496" "2554" "2932" "3054" "2343" "2427" "2933"
##
## [[2]]
##  [1] "173"  "516"  "1232" "69"   "1895" "966"  "1975" "2562" "1974" "2406"
## [11] "925"  "1076" "1132" "1673" "3179" "1580" "844"  "47"   "2798" "3036"
## [21] "548"  "952"  "2277" "2407" "2408" "2830"
##
## [[3]]
##  [1] "979"  "1345" "2311" "1054" "2232" "765"  "1103" "2159" "42"   "108"
## [11] "81"   "1237" "1620" "2289" "3160" "17"   "595"  "1300" "1346" "1543"
## [21] "1570" "2202" "2225" "3195" "214"  "763"  "2160" "2517" "2809" "2960"
## [31] "18"   "249"  "1079" "1123" "1408" "1571" "2831"
##
## [[4]]
##  [1] "128"  "359"  "464"  "471"  "736"  "822"  "885"  "961"  "1030" "1116"
## [11] "2473" "1570" "2563" "2470" "1932" "2071" "978"  "2265" "2689" "2245"
## [21] "194"  "3179"
par(mfrow=c(1,1))

#Participants with Zero SDI on measures of interest at specific time-points
lagdat <- lagdat [order(lagdat$id),]
zerosdi.spuss<- cbind(lagdat$id[lagdat$SPUSS.sdi==0],
                      lagdat$time[lagdat$SPUSS.sdi==0])
colnames( zerosdi.spuss ) <- c("Zero SDI ID","SPUSS At Time Point:")
zerosdi.tm<- cbind(lagdat$id[lagdat$TM.sdi==0],
                   lagdat$time[lagdat$TM.sdi==0])
colnames( zerosdi.tm ) <- c("Zero SDI ID","TM At Time Point:")
zerosdi.sacq<- cbind(lagdat$id[lagdat$SACQ.sdi==0],
                     lagdat$time[lagdat$SACQ.sdi==0])
zerosdi.sacq<- as.data.frame(na.omit(zerosdi.sacq))
colnames( zerosdi.sacq) <- c("Zero SDI ID","SACQ At Time Point:")
zerosdi.cesd<- cbind(lagdat$id[lagdat$CESD.sdi==0],
                     lagdat$time[lagdat$CESD.sdi==0])
zerosdi.cesd<- as.data.frame(na.omit(zerosdi.cesd))
colnames( zerosdi.cesd) <- c("Zero SDI ID","CESD At Time Point:")


pander ( list(zerosdi.spuss,zerosdi.tm,zerosdi.sacq, zerosdi.cesd ))
```

Zero SDI ID	SPUSS At Time Point:	Zero SDI ID	TM At Time Point:
21	1	21	1
21	2	21	2
477	2	148	1
677	2	477	2
877	0	533	1
918	0	760	2
951	2	969	1
969	1	1032	2
1025	2	1119	2
1032	2	1273	2
1119	1	1484	1
1119	2	1587	0
1273	2	1587	2
1303	1	1639	1
1303	2	1830	2
1391	1	1912	1
1398	1	2335	1
1484	1	2403	1
1484	2	2436	1
1829	1	Zero SDI ID	SACQ At Time Point:
1830	0	21	0
1830	1	148	0
1830	2	1273	1
1912	1	Zero SDI ID	CESD At Time Point:
2116	1	790	2
2199	2	876	0
2453	2	876	2
2465	1	918	2
2522	1	957	0
2524	1	1092	0
2562	1	1278	2
2651	0	1409	0
2854	1	1658	0

2884	1	1726	0
2884	2	1773	2
		1835	0
		1835	2
		1977	0
		2085	0
		2412	0
		2538	0
		2544	2
		2817	0

```
lagdat <- lagdat [lagdat$id != 21, ]
lagdat <- lagdat [lagdat$id != 1273, ]
lagdat <- lagdat [lagdat$id != 1303, ]
lagdat <- lagdat [lagdat$id != 1830, ]
lagdat <- lagdat [lagdat$id != 2884, ]

dat.inclusive$exclusion [dat.inclusive$id == 21] <- 4
dat.inclusive$exclusion [dat.inclusive$id == 1273] <- 4
dat.inclusive$exclusion [dat.inclusive$id == 1303] <- 4
dat.inclusive$exclusion [dat.inclusive$id == 1830] <- 4
dat.inclusive$exclusion [dat.inclusive$id == 2884] <- 4
##Those with inclusion of 1 and no NAs in controls vs those not
##Does not include those missing SPUSS or TM since removed at missed time point
## Variables of interest: HS, Income, Gender, University
dat.inclusive$inclusion <- 1
dat.inclusive$inclusion[dat.inclusive$exclusion!=1] <- 0
dat.inclusive$inclusion[is.na(dat.inclusive$ahs_avg)] <- 0
dat.inclusive$inclusion[is.na(dat.inclusive$agender)] <- 0
dat.inclusive$inclusion[is.na(dat.inclusive$income)] <- 0

dat.inclusive$inclusion<- factor(dat.inclusive$inclusion,levels = c(0,1),labels = c("Excluded",
                                                                           "Included"))
dat.inclusive$agender <- ordered(dat.inclusive$agender,levels = c(1,2),labels = c("Male", "Female"))
dat.inclusive <- dat.inclusive[!is.na(dat.inclusive$agender ),]
dat.inclusive$univ <- factor(dat.inclusive$univ,levels = c(1,2,3,4,5,6),
                             labels = c("WLU","Guelph","UTE","UTG","York", "MUN"))

pander(t.test(ahs_avg ~ inclusion, data = dat.inclusive ), plain.ascii = TRUE , digits = 2)
```

Welch Two Sample t-test: `ahs_avg` by `inclusion` (continued below)

Test statistic	df	P value	Alternative hypothesis
-6.5	2459	1.08e-10 *	two.sided

mean in group Excluded	mean in group Included
82	84

```
cohen.d(ahs_avg ~ inclusion, data = dat.inclusive)
##
## Cohen's d
##
## d estimate: -0.2531512 (small)
## 95 percent confidence interval:
##        inf        sup
## -0.3291746 -0.1771279
hsplot<-ggplot(data = dat.inclusive,
               aes(x = inclusion, y = ahs_avg,group = inclusion,  fill = inclusion))+
  geom_boxplot() +theme(legend.position="none", axis.title.x = element_blank())+
  labs( title = "Self-Reported High School Averages of Included and Excluded Students") +
  scale_y_continuous(name = "High School Graduating Averege %",limits=c(0, 100))
hsplot
## Warning: Removed 184 rows containing non-finite values (stat_boxplot).
pander(chisq.test (table(dat.inclusive$income, dat.inclusive$inclusion)))
```

Pearson's Chi-squared test: `table(dat.inclusive$income, dat.inclusive$inclusion)`

Test statistic	df	P value
1.956	3	0.5816

```
paste0("CRAMERV Income Exclusion: ", CramerV(table(dat.inclusive$income, dat.inclusive$inclusion)))
## [1] "CRAMERV Income Exclusion: 0.0261696307401406"
inplot<-ggplot(data = dat.inclusive, aes(x = income, y = ..count..))+
  geom_bar(aes( fill = inclusion), position=position_dodge()) +
  labs( title = "Income Level Porportions of  Included and Excluded Students",
        y = "Frequency Count", x = "Self-Reported Income Level", fill = "Inclusion:")
inplot
## Warning: Removed 19 rows containing non-finite values (stat_count).
pander(chisq.test (table(dat.inclusive$agender, dat.inclusive$inclusion)))
```

Pearson's Chi-squared test with Yates' continuity correction: `table(dat.inclusive$agender, dat.inclusive$inclusion)`

Test statistic	df	P value
42.73	1	6.299e-11 * * *

```
paste0("CRAMERV Gender Exclusion: ", CramerV(table(dat.inclusive$agender, dat.inclusive$inclusion)))
## [1] "CRAMERV Gender Exclusion: 0.122605396406274"
```

```
genderplot<-ggplot(data = dat.inclusive,aes(x = agender, y = ..count..))+
  geom_bar(aes( fill = inclusion),position=position_dodge()) +
  labs( title = "Gender Porportions of  Included and Excluded Students",
        y = "Frequency Count", x = "", fill = "Inclusion:")
genderplot
pander(chisq.test (table(dat.inclusive$univ, dat.inclusive$inclusion)))
```

Pearson's Chi-squared test: `table(dat.inclusive$univ, dat.inclusive$inclusion)`

Test statistic	df	P value
29.17	5	2.146e-05 * * *

```
paste0("CRAMERV Uni Exclusion: ", CramerV(table(dat.inclusive$univ, dat.inclusive$inclusion)))
## [1] "CRAMERV Uni Exclusion: 0.100730718073896"
uniplot<-ggplot(data = dat.inclusive,aes(x = univ, y = ..count..))+
  geom_bar(aes( fill = inclusion),position=position_dodge()) +
  labs( title = "Porportions of  Included and Excluded Students From Universities",
        y = "Frequency Count", x = "", fill = "Inclusion:")
uniplot
#mosaic plot of university porportions
mosaicplot(table(dat.inclusive$univ, dat.inclusive$inclusion),
           type = "pearson", shade=TRUE)
##Those to have provided data upto the last data collection point
## Versus all other included participants.
## Variables of interest: HS, Income, Gender, University

datincluded <- dat.inclusive[dat.inclusive$inclusion=="Included",]
datincluded$attrition <- 1
datincluded$attrition[datincluded$yesT5==0] <- 0
datincluded$attrition<- factor(datincluded$attrition,levels = c(0,1),
                               labels = c("Attrited","Completed"))

table(datincluded$yesT5)
##
##   0   1
## 804 618
ddply(datincluded,~attrition,summarise,mean=mean(ahs_avg),sd=sd(ahs_avg))
##   attrition     mean       sd
## 1  Attrited 83.40539 5.928042
## 2 Completed 84.73280 5.946015
pander(t.test(ahs_avg ~ attrition, data = datincluded ), plain.ascii = TRUE , digits = 2)
```

Welch Two Sample t-test: `ahs_avg` by `attrition` (continued below)

Test statistic	df	P value	Alternative hypothesis
-4.2	1325	3.126e-05 *	two.sided

mean in group Attrited	mean in group Completed
83	85

```
cohen.d(ahs_avg ~ attrition, data = datincluded)
##
## Cohen's d
##
## d estimate: 0.2235376 (small)
## 95 percent confidence interval:
##       inf       sup
## 0.1182748 0.3288004
hsplot1<-ggplot(data = datincluded,
                aes(x = attrition, y = ahs_avg,group = attrition,  fill = attrition))+
  geom_boxplot() +theme(legend.position="none", axis.title.x = element_blank()) +
labs( title = "Self-Reported High School Averages of Completed Versus Attrited Participants") +
  scale_y_continuous(name = "High School Graduating Averege %",limits=c(60, 100))
hsplot1
pander(chisq.test (table(datincluded$income, datincluded$attrition)))
```

Pearson's Chi-squared test: `table(datincluded$income, datincluded$attrition)`

Test statistic	df	P value
0.8933	3	0.827

```
paste0("CRAMERV Income Attrition: ", CramerV(table(datincluded$income, datincluded$attrition)))
## [1] "CRAMERV Income Attrition: 0.0250645554333561"
inplot1<-ggplot(data = datincluded, aes(x = income, y = ..count..))+
  geom_bar(aes( fill = attrition), position=position_dodge()) +
  labs( title = "Income Level Porportions of  Completed Versus Attrited Participants",
        y = "Frequency Count", x = "Self-Reported Income Level", fill = "Attrition:")
inplot1
pander(chisq.test (table(datincluded$agender, datincluded$attrition)))
```

Pearson's Chi-squared test with Yates' continuity correction: `table(datincluded$agender, datincluded$attrition)`

Test statistic	df	P value
5.745	1	0.01653 *

```
paste0("CRAMERV Gender Attrition: ", CramerV(table(datincluded$agender, datincluded$attrition)))
## [1] "CRAMERV Gender Attrition: 0.0650221348913101"
genderplot1<-ggplot(data = datincluded,aes(x = agender, y = ..count..))+
  geom_bar(aes( fill = attrition),position=position_dodge()) +
```

```r
  labs( title = "Gender Porportions of  Completed Versus Attrited Participants",
        y = "Frequency Count", x = "", fill = "Attrition:")
genderplot1
pander(chisq.test (table(datincluded$univ, datincluded$attrition)))
```

Pearson's Chi-squared test: `table(datincluded$univ, datincluded$attrition)`

Test statistic	df	P value
13.47	5	0.01932 *

```r
paste0("CRAMERV Uni Attrition: ", CramerV(table(datincluded$univ, datincluded$attrition)))
## [1] "CRAMERV Uni Attrition: 0.097343445995771"
uniplot1<-ggplot(data = datincluded,aes(x = univ, y = ..count..))+
  geom_bar(aes( fill = attrition),position=position_dodge()) +
  labs( title = "Frequency Count of Completed Versus Attrited Participants From Universities",
        y = "Frequency Count", x = "", fill = "Attrition:")
uniplot1
#mosaic plot of university porportions
mosaicplot(table(datincluded$univ, datincluded$attrition),
           type = "pearson", shade=TRUE)
dat.inclusive$sample<- factor(dat.inclusive$sample,levels = c(1,2),
                              labels = c("2004 Cohort","2005 Cohort"))
datincluded$sample<- factor(datincluded$sample,levels = c(1,2),
                            labels = c("2004 Cohort","2005 Cohort"))

# gender between cohorts?
pander(chisq.test (table(dat.inclusive$sample, dat.inclusive$agender)))
```

Pearson's Chi-squared test with Yates' continuity correction: `table(dat.inclusive$sample, dat.inclusive$agender)`

Test statistic	df	P value
33.37	1	7.634e-09 * * *

```r
pander(table(dat.inclusive$sample, dat.inclusive$agender))
```

	Male	Female
2004 Cohort	404	671
2005 Cohort	877	923

```r
paste0("CRAMERV Gender Cohort: ", CramerV(table(dat.inclusive$sample, dat.inclusive$agender)))
## [1] "CRAMERV Gender Cohort: 0.10845240487107"
cohortg<-ggplot(data = dat.inclusive, aes(x = sample, y = ..count..))+
  geom_bar(aes( fill = agender), position=position_dodge()) +
  labs( title = "Porportions of  Genders in the 2004 and 2005 Cohorts",
        y = "Frequency Count", x = "Cohort", fill = "Gender:") +
  scale_fill_brewer(palette = "Set1")
cohortg
#high school GPA between cohorts
pander(t.test(ahs_avg ~ sample, data = dat.inclusive ), plain.ascii = TRUE , digits = 2)
```

Welch Two Sample t-test: `ahs_avg` by `sample` (continued below)

Test statistic	df	P value	Alternative hypothesis
3.6	2311	0.0003857 *	two.sided

mean in group 2004 Cohort	mean in group 2005 Cohort
84	83

```r
cohen.d(ahs_avg ~ sample, data = dat.inclusive)
##
## Cohen's d
##
## d estimate: -0.1425075 (negligible)
## 95 percent confidence interval:
##        inf        sup
## -0.2212043 -0.0638107
ddply(dat.inclusive,~sample,summarise,mean=mean(ahs_avg, na.rm = TRUE),sd=sd(ahs_avg, na.rm = TRUE))
##        sample     mean       sd
## 1 2004 Cohort 83.76995 5.950824
## 2 2005 Cohort 82.86354 7.021879
cohorths<-ggplot(data = dat.inclusive, aes(x = sample, y = ahs_avg, fill = sample))+
  geom_boxplot() +theme(legend.position="none", axis.title.x = element_blank())+
  labs( title = "Self-Reported High School Averages of the 2004 and 2005 Cohorts") +
  scale_y_continuous(name = "High School Graduating Averege %",limits=c(0, 100))
cohorths
## Warning: Removed 184 rows containing non-finite values (stat_boxplot).
#income between cohorts
pander(chisq.test (table(dat.inclusive$income, dat.inclusive$sample)))
```

Pearson's Chi-squared test: `table(dat.inclusive$income, dat.inclusive$sample)`

Test statistic	df	P value
7.64	3	0.05407

```r
pander(table(dat.inclusive$income, dat.inclusive$sample))
```

2004 Cohort	2005 Cohort
123	219
609	1037
284	487

49	48

```
paste0("CRAMERV Income Cohort: ", CramerV(table(dat.inclusive$income, dat.inclusive$sample)))
## [1] "CRAMERV Income Cohort: 0.0517214831205818"
cohortincome<-ggplot(data = dat.inclusive, aes(x = income, y = ..count..))+
  geom_bar(aes( fill = sample), position=position_dodge()) +
  labs( title = "Income Level Porportions of 2004 and 2005 Cohorts",
        y = "Frequency Count", x = "Self-Reported Income Level", fill = "Cohort:")
cohortincome
## Warning: Removed 19 rows containing non-finite values (stat_count).
#university porportions
pander(chisq.test (table(dat.inclusive$univ, dat.inclusive$sample)))
```

Pearson's Chi-squared test: `table(dat.inclusive$univ, dat.inclusive$sample)`

Test statistic	df	P value
79.41	5	1.116e-15 * * *

```
pander(table(dat.inclusive$univ, dat.inclusive$sample))
```

	2004 Cohort	2005 Cohort
WLU	180	374
Guelph	210	342
UTE	163	168
UTG	196	208
York	188	306
MUN	138	402

```
paste0("CRAMERV Uni Cohort: ", CramerV(table(dat.inclusive$univ, dat.inclusive$sample)))
## [1] "CRAMERV Uni Cohort: 0.166193967711101"
cohortuni<-ggplot(data = dat.inclusive,aes(x = univ, y = ..count..))+
  geom_bar(aes( fill = sample),position=position_dodge()) +
  labs( title = "Frequency of Students From Universities in the 2004 and 2005 Cohorts",
        y = "Frequency Count", x = "", fill = "Cohort:")
cohortuni
#mosaic plot of university porportions
mosaicplot(table(dat.inclusive$univ, dat.inclusive$sample),
           type = "pearson", shade=TRUE)
#Inclusion between cohorts?
pander(chisq.test (table(dat.inclusive$sample, dat.inclusive$inclusion)))
```

Pearson's Chi-squared test with Yates' continuity correction: `table(dat.inclusive$sample, dat.inclusive$inclusion)`

Test statistic	df	P value
52.29	1	4.784e-13 * * *

```
paste0("CRAMERV Inclusion Cohort: ", CramerV(table(dat.inclusive$sample, dat.inclusive$inclusion)))
## [1] "CRAMERV Inclusion Cohort: 0.135583371004912"
cohorti<-ggplot(data = dat.inclusive, aes(x = sample, y = ..count..))+
  geom_bar(aes( fill = inclusion), position=position_dodge()) +
  labs( title = "Cohort Porportions of  Included and Excluded Students",
        y = "Frequency Count", x = "Cohort", fill = "Inclusion:")
cohorti

#Attrition difference between cohorts?
pander(chisq.test (table(datincluded$sample, datincluded$attrition)))
```

Pearson's Chi-squared test with Yates' continuity correction: `table(datincluded$sample, datincluded$attrition)`

Test statistic	df	P value
8.119	1	0.00438 * *

```
paste0("CRAMERV Attrition Cohort: ", CramerV(table(datincluded$sample, datincluded$attrition)))
## [1] "CRAMERV Attrition Cohort: 0.0769921042883561"
cohorta<-ggplot(data = datincluded, aes(x = sample, y = ..count..))+
  geom_bar(aes( fill = attrition), position=position_dodge()) +
  labs( title = "Cohort Porportions of  Completed Versus Attrited Participants",
        y = "Frequency Count", x = "Cohort", fill = "Attrition:")
cohorta
ss1 <- ggplot(data = lagdat, aes(x = time + 1 , y = SACQ.mean, group = id))+
 geom_line( aes(col=univ),size = 1.2, alpha = .15) +
  facet_grid( ~ lagdat$univ) +
  geom_smooth(aes(col=univ), size = 0.9, group = 1, se = FALSE, method = "lm") +
  stat_summary(aes(group = 1, col=univ), geom = "point", fun.y = mean, shape = 20, size = 3.5) +
  labs(colour = "University") + xlab("Academic Year") + ylab("Mean SACQ Scores") +
  theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Students' Mean Adjustment Scores Across Six Univeristies Over Time")
ss1
## Warning: Removed 1056 rows containing non-finite values (stat_smooth).
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
## Warning: Removed 1056 rows containing missing values (geom_path).
ss2 <- ggplot(data = lagdat, aes(x = time + 1 , y = CESD.mean, group = id))+
 geom_line( aes(col=univ),size = 1.2, alpha = .15) +
  facet_grid(~ lagdat$univ) +
  geom_smooth(aes(col=univ), size = 0.9, group = 1, se = FALSE, method = "lm") +
  stat_summary(aes(group = 1, col=univ), geom = "point", fun.y = mean, shape = 20, size = 3.5) +
  labs(colour = "University") + xlab("Academic Year") + ylab("Mean CESD Scores") +
```

```
  theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Students' Mean Depression Scores Across Six Univeristies Over Time")
ss2
## Warning: Removed 1036 rows containing non-finite values (stat_smooth).
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
## Warning: Removed 1032 rows containing missing values (geom_path).
ss4 <- ggplot(data = lagdat, aes(x = time + 1 , y = PSS.mean, group = id))+
 geom_line( aes(col=univ),size = 1.2, alpha = .15) +
  facet_grid( ~ lagdat$univ) +
  geom_smooth(aes(col=univ), size = 0.9, group = 1, se = FALSE, method = "lm") +
  stat_summary(aes(group = 1, col=univ), geom = "point", fun.y = mean, shape = 20, size = 3.5) +
  labs(colour = "University") + xlab("Academic Year") + ylab("Mean PSS Scores") +
  theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Students' Mean Perceived Stress Scores Across Six Univeristies Over Time")
ss4
## Warning: Removed 1036 rows containing non-finite values (stat_smooth).
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
## Warning: Removed 1036 rows containing missing values (geom_path).
ss5<- ggplot(data = lagdat, aes(x = semester + 1 , y = TM.mean, group = id))+
  geom_line( aes(col=univ),size = 1.2, alpha = .15) +
  facet_grid( ~ lagdat$univ) +
  geom_smooth(aes(col=univ), size = 0.9, group = 1, se = FALSE, method = "lm") +
  stat_summary(aes(group = 1, col=univ), geom = "point", fun.y = mean, shape = 20, size = 3.5) +
  labs(colour = "University") + xlab("Academic Semester") + ylab("Mean TM Scores") +
  theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Students' Mean Time-Management Scores Across Six Univeristies Over Time")
ss5
s6 <- ggplot(data = dat.long[dat.long$time<5,], aes(x = time , y = SPUSS.mean, group = id))+
  geom_line( aes(col=univ),size = 1.2, alpha = .15) +
  facet_grid( ~ univ) +
  geom_smooth(aes(col=univ), size = 0.9, group = 1, se = FALSE, method = "lm") +
  stat_summary(aes(group = 1, col=univ), geom = "point", fun.y = mean, shape = 20, size = 3.5) +
  labs(colour = "University") + xlab("Academic Year") + ylab("Mean SPUSS Scores") +
  theme(plot.title = element_text(hjust = 0.5)) + xlim(0,2) +
  ggtitle("Students' Perception of Support and Structure Scores Across Six Univeristies Over Time")
s6
## Warning: Removed 547 rows containing non-finite values (stat_smooth).
## Warning: Removed 547 rows containing non-finite values (stat_summary).
## Warning: Removed 547 rows containing missing values (geom_path).
ss6<- ggplot(data = lagdat, aes(x = semester + 1 , y = SPUSS.mean, group = id))+
  geom_line( aes(col=univ),size = 1.2, alpha = .15) +
  facet_grid( ~ lagdat$univ) +
  geom_smooth(aes(col=univ), size = 0.9, group = 1, se = FALSE, method = "lm") +
  stat_summary(aes(group = 1, col=univ), geom = "point", fun.y = mean, shape = 20, size = 3.5) +
  labs(colour = "University") + xlab("Academic Semester") + ylab("Mean SPUSS Scores") +
  theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Students' Perception of Support and Structure Scores Across Six Univeristies Over Time")
ss6
title1=textGrob("Distribution of Process and Outcome Measures at each Longitudinal Collection Timepoint",
  gp=gpar(fontface="bold"))
his1 <- ggplot(lagdat, aes(SPUSS.mean)) + geom_histogram(fill = "magenta4") +facet_wrap(~(time+1)) +
  labs(x = "SPUSS Mean Scores", y = "Frequency Count") +
  theme_light()

his2 <- ggplot(lagdat, aes(TM.mean)) + geom_histogram(fill = "magenta4") +facet_wrap(~(time+1)) +
  labs(x = "Time-Management Mean Scores", y = "Frequency Count") +
  theme_light() + scale_y_continuous(breaks=c(0,50,100))

his3 <- ggplot(lagdat, aes(SACQ.mean)) + geom_histogram(fill = "olivedrab3") +facet_wrap(~(time+1)) +
  labs(x = "SACQ Mean Scores", y = "Frequency Count") +
  theme_light()

his4 <- ggplot(lagdat, aes(CESD.mean)) + geom_histogram(fill = "olivedrab3") +facet_wrap(~(time+1)) +
  labs(x = "CESD Mean Scores", y = "Frequency Count") +
  theme_light()

his5 <- ggplot(lagdat, aes(PSS.mean)) + geom_histogram(fill = "olivedrab3", binwidth = .25) +
  facet_wrap(~(time+1)) +  labs(x = "PSS Mean Scores", y = "Frequency Count") +
  theme_light()

grid.arrange(his1, his2, his3, his4, his5, top = title1, ncol = 1)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1056 rows containing non-finite values (stat_bin).
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1036 rows containing non-finite values (stat_bin).
## Warning: Removed 1036 rows containing non-finite values (stat_bin).
```

```
his8<- ggplot(lagdat[unique(lagdat$id),],
              aes(ahs_avg)) + geom_histogram(fill = "magenta4", binwidth = 2) +
   labs(x = "Graduating Average",
        y = "Frequency Count",title = " Self-Reported Highschool Graduating GPA") +
  theme_light()
b1 <- ggplot(lagdat[unique(lagdat$id),],
              aes(incomef)) + geom_bar(fill = "darkblue") +theme_light()+
  labs(x = "Self-Reported Income Level", y = "Frequency Count",title = " Self-Reported Income Levels")
b2 <- ggplot(lagdat[unique(lagdat$id),],
             aes(agenderf)) + geom_bar(fill =4:5 ) +theme_light() +
  labs(x = "Gender",  y = "Frequency Count",title = " Gender")

grid.arrange(his8, b1, b2, ncol = 3)
#calculating Demographics

paste ("Average Highschool GPA: ", round(mean(lagdat$ahs_avg[unique(lagdat$id)]),1))
## [1] "Average Highschool GPA:  84.1"
pander(table(lagdat$incomef[unique(lagdat$id)]) %>% prop.table()*100)
```

Below Average	Average	Above Average	Well Above Average
12.33	55.84	27.89	3.943

```
pander(table(lagdat$agenderf[unique(lagdat$id)]) %>% prop.table()*100)
```

Male	Female
39.57	60.43

```
#using stargazer for summary statistics.

stargazer(lagdat[lagdat$time==0,c("SACQ.mean","PSS.mean","CESD.mean")],
          type = "text", nobs = TRUE, mean.sd = TRUE, median = TRUE,
           out = "demyear1.txt", digits = 2, iqr = FALSE,
          covariate.labels=c("SACQ Mean Scores", "PSS Mean Scores", "CESD Mean Scores"),
          title = "Summary Statistics of Outcome Variables Spring of First Year")
##
## Summary Statistics of Outcome Variables Spring of First Year
## =====================================================================
## Statistic          N   Mean St. Dev. Min  Pctl(25) Median Pctl(75) Max
## ---------------------------------------------------------------------
## SACQ Mean Scores 1,115 5.95   1.12   2.61   5.17    6.04    6.76   8.68
## PSS Mean Scores  1,120 1.59   0.73   0.00   1.00    1.50    2.00   4.00
## CESD Mean Scores 1,126 0.84   0.57   0.00   0.40    0.70    1.15   2.85
## ---------------------------------------------------------------------
stargazer(lagdat[lagdat$time==1,c("SACQ.mean","PSS.mean","CESD.mean")],
          type = "text", nobs = TRUE, mean.sd = TRUE, median = TRUE,
          out = "demyear2.txt", digits = 2, iqr = FALSE,
          covariate.labels=c("SACQ Mean Scores", "PSS Mean Scores", "CESD Mean Scores"),
          title = "Summary Statistics of Outcome Variables Spring of Second Year")
##
## Summary Statistics of Outcome Variables Spring of Second Year
## ===================================================================
## Statistic         N  Mean St. Dev. Min  Pctl(25) Median Pctl(75) Max
## -------------------------------------------------------------------
## SACQ Mean Scores 621 5.81   1.14   2.41   5.08    5.85    6.63   8.79
## PSS Mean Scores  632 1.59   0.74   0.00   1.00    1.50    2.00   3.75
## CESD Mean Scores 625 0.83   0.54   0.05   0.40    0.70    1.20   2.70
## -------------------------------------------------------------------
stargazer(lagdat[lagdat$time==2,c("SACQ.mean","PSS.mean","CESD.mean")],
          type = "text", nobs = TRUE, mean.sd = TRUE, median = TRUE,
          out = "demyear3.txt", digits = 2, iqr = FALSE,
          covariate.labels=c("SACQ Mean Scores", "PSS Mean Scores", "CESD Mean Scores"),
          title = "Summary Statistics of Outcome Variables Spring of Third Year")
##
## Summary Statistics of Outcome Variables Spring of Third Year
## ===================================================================
## Statistic         N  Mean St. Dev. Min  Pctl(25) Median Pctl(75) Max
## -------------------------------------------------------------------
## SACQ Mean Scores 397 5.69   1.07   2.14   5.00    5.77    6.51   8.39
## PSS Mean Scores  401 1.46   0.76   0.00   1.00    1.50    2.00   4.00
## CESD Mean Scores 402 0.76   0.54   0.00   0.35    0.62    1.05   2.80
## -------------------------------------------------------------------
#Process Variables:

stargazer(lagdat[lagdat$time==0,c("TM.mean","SPUSS.mean")],
          type = "text", nobs = TRUE, mean.sd = TRUE, median = TRUE,
          out = "processdemtablefall.txt", digits = 2, iqr = FALSE,
          covariate.labels=c("TMU Mean Scores", "SPUSS Mean Scores"),
          title = "Summary Statistics of Process Variables Fall of First year")
##
## Summary Statistics of Process Variables Fall of First year
## ======================================================================
```

```
## Statistic           N   Mean St. Dev. Min  Pctl(25) Median Pctl(75) Max
## ---------------------------------------------------------------------------
## TMU Mean Scores   1,272 2.24   0.66   0.32   1.82    2.23    2.68   4.00
## SPUSS Mean Scores 1,272 6.32   1.03   2.25   5.61    6.35    7.05   9.00
## ---------------------------------------------------------------------------
stargazer(lagdat[lagdat$time==1,c("TM.mean","SPUSS.mean")],
          type = "text", nobs = TRUE, mean.sd = TRUE, median = TRUE,
          out = "processdemtablespring.txt", digits = 2, iqr = FALSE,
          covariate.labels=c("TMU Mean Scores", "SPUSS Mean Scores"),
          title = "Summary Statistics of Process Variables Spring of First year")
##
## Summary Statistics of Process Variables Spring of First year
## ===========================================================================
## Statistic           N   Mean St. Dev. Min  Pctl(25) Median Pctl(75) Max
## ---------------------------------------------------------------------------
## TMU Mean Scores   1,215 2.16   0.71   0.10   1.73    2.14    2.64   4.00
## SPUSS Mean Scores 1,215 6.26   1.09   2.70   5.50    6.25    7.00   9.00
## ---------------------------------------------------------------------------
stargazer(lagdat[lagdat$time==2,c("TM.mean","SPUSS.mean")],
          type = "text", nobs = TRUE, mean.sd = TRUE, median = TRUE,
          out = "processdemtableyear2.txt", digits = 2, iqr = FALSE,
          covariate.labels=c("TMU Mean Scores", "SPUSS Mean Scores"),
          title = "Summary Statistics of Process Variables Spring of Second year")
##
## Summary Statistics of Process Variables Spring of Second year
## =========================================================================
## Statistic          N  Mean St. Dev. Min  Pctl(25) Median Pctl(75) Max
## -------------------------------------------------------------------------
## TMU Mean Scores   702 2.23   0.69   0.50   1.73    2.23    2.67   4.00
## SPUSS Mean Scores 702 6.32   1.07   2.30   5.58    6.35    7.10   8.90
## -------------------------------------------------------------------------
#Another example of using functions to streamline/make more efficient the coding process
#Rob I think you'll appreciate this - I cut down roughly 1000 lines by writing this function
#vs doing the assumptions individually at the end of each MLM

assumptioncheck <-function (dataset, outcome,  finalmodel, slope = TRUE) {

  #getting the error residuals in a dataframe with IDs to locate extreme values
  eij <- as.data.frame(cbind(dataset$id,residuals(finalmodel)))
  rownames(eij) <- c()
  colnames(eij) <- c("id", "eij")

  #getting the random effect residuals in a dataframe with IDs to locate extreme values
  tempzeta <- random.effects(finalmodel)

  if(slope){
    univ.zeta0i <- tempzeta$univ[,1]
    univ.zeta1i <- tempzeta$univ[,2]
  }

  id.zeta0i<- as.data.frame(cbind(rownames (tempzeta$id),tempzeta$id[,1]))
  colnames(id.zeta0i) <- c("id", "zeta0i")
  id.zeta0i$zeta0i <- as.numeric(levels(id.zeta0i$zeta0i )[id.zeta0i$zeta0i ]) #factor to numeric

  if(slope){
    id.zeta1i<- as.data.frame(cbind(rownames (tempzeta$id),tempzeta$id[,2]))
    colnames(id.zeta1i) <- c("id", "zeta1i")
    id.zeta1i$zeta1i <- as.numeric(levels(id.zeta1i$zeta1i )[id.zeta1i$zeta1i]) #factor to numeric


    p1 <- ggplot(eij, aes(x =  eij)) +
      geom_histogram(aes(y = ..density.., fill=..count..)) +
      stat_function(fun = dnorm, colour = "red",
                    args = list(mean = mean(eij$eij, na.rm = TRUE),
                                sd = sd(eij$eij, na.rm = TRUE))) +
      labs(y = "Distribution of Residuals", x = "Error Residual", colour = "Frequency",
           title = "Distribution of Error Residuals",
           caption = "The equavalent normal distribution is shown in red.")



    p2 <- ggplot(id.zeta0i, aes(x =  zeta0i)) +
      geom_histogram(aes(y = ..density.., fill=..count..)) +
      stat_function(fun = dnorm, colour = "red",
                    args = list(mean = mean(id.zeta0i$zeta0i, na.rm = TRUE),
                                sd = sd(id.zeta0i$zeta0i, na.rm = TRUE)))+
      labs(y = "Distribution of Residuals", x = "Intercept Residual (Zeta0i)", colour = "Frequency",
```

```
        title = "Distribution of Intercept Residuals")


  p3 <- ggplot(id.zeta1i, aes(x =  zeta1i)) +
    geom_histogram(aes(y = ..density.., fill=..count..)) +
    stat_function(fun = dnorm, colour = "red",
                  args = list(mean = mean(id.zeta1i$zeta1i, na.rm = TRUE),
                              sd = sd(id.zeta1i$zeta1i, na.rm = TRUE)))+
    labs(y = "Distribution of Residuals", x = "Slope Residual (Zeta1i)", colour = "Frequency",
         title = "Distribution of Slope Residuals")


  grid.arrange(p1, p2, p3, ncol = 3)
}

if(!slope) {

  p1 <- ggplot(eij, aes(x =  eij)) +
    geom_histogram(aes(y = ..density.., fill=..count..)) +
    stat_function(fun = dnorm, colour = "red",
                  args = list(mean = mean(eij$eij, na.rm = TRUE),
                              sd = sd(eij$eij, na.rm = TRUE))) +
    labs(y = "Distribution of Residuals", x = "Error Residual", colour = "Frequency",
         title = "Distribution of Error Residuals",
         caption = "The equavalent normal distribution is shown in red.")


  p2 <- ggplot(id.zeta0i, aes(x =  zeta0i)) +
    geom_histogram(aes(y = ..density.., fill=..count..)) +
    stat_function(fun = dnorm, colour = "red",
                  args = list(mean = mean(id.zeta0i$zeta0i, na.rm = TRUE),
                              sd = sd(id.zeta0i$zeta0i, na.rm = TRUE)))+
    labs(y = "Distribution of Residuals", x = "Intercept Residual (Zeta0i)", colour = "Frequency",
         title = "Distribution of Intercept Residuals")

  grid.arrange(p1,p2, ncol = 2)
}

## Checking assumptions - visualizing  extreme residuals on either tail
layout(matrix(c(1), 1, 1, byrow = TRUE))
eij$std_eij <- eij$eij/sd(eij$eij, na.rm = TRUE)
eij$fitted <- fitted(finalmodel)
eij<- eij [order(eij$eij),]
eijextreme <- eij[1:7,]
eij<- eij [order(eij$eij, decreasing = TRUE),]
eijextreme <- rbind(eijextreme,eij[1:7,])

plot(eij$id, eij$std_eij, col='blue',
     main = "Visualizing Extreme Residuals Accross all Individual Cases",
     xlab = "Participant ID", ylab = "Standardized Error Residual")
abline(h=0)
text(eijextreme$id, y = eijextreme$eij/sd(eij$eij, na.rm = TRUE),
     labels = eijextreme$id, pos = 4, offset = 0.2,  cex = 0.7)

# extracting ID's from the ID school combination
regexp <- "[[:digit:]]+"
id.zeta0i$id <- as.numeric(str_extract(id.zeta0i$id, regexp))
if(slope) id.zeta1i$id <- as.numeric(str_extract(id.zeta1i$id, regexp))

#plotting standardized intercept errors
layout(matrix(c(1,1,2,2), 2, 2, byrow = TRUE))

id.zeta0i$std_zeta0 <- id.zeta0i$zeta0i/sd(id.zeta0i$zeta0i)
id.zeta0i <- id.zeta0i[order(id.zeta0i$zeta0i),]
extremezeta0i <- id.zeta0i[1:5,]
id.zeta0i <- id.zeta0i[order(id.zeta0i$zeta0i,decreasing = TRUE),]
extremezeta0i <- rbind(extremezeta0i, id.zeta0i[1:5,])


plot(id.zeta0i$id, id.zeta0i$std_zeta0,cex=1, pch = 1, col = 'blue',
     main = "Visualizing Extreme Intercept Residuals Accross all Individual Cases",
     xlab = "Participant ID", ylab = "Standardized Intercept Residual")
abline(h=0, lwd = 2)
text(extremezeta0i$id, y = extremezeta0i$zeta0i/sd(id.zeta0i$zeta0i),
     labels = extremezeta0i$id, pos = 4, offset = 0.2,  cex = 0.7)
```

```r
#plotting standardized slope errors
if(slope){
  id.zeta1i$std_zeta1 <- id.zeta1i$zeta1i/sd(id.zeta1i$zeta1i)
  id.zeta1i <- id.zeta1i[order(id.zeta1i$zeta1i),]
  extremezeta1i <- id.zeta1i[1:5,]
  id.zeta1i <- id.zeta1i[order(id.zeta1i$zeta1i,decreasing = TRUE),]
  extremezeta1i <- rbind(extremezeta1i, id.zeta1i[1:5,])


  plot(id.zeta1i$id, id.zeta1i$std_zeta1,cex=1, pch = 1, col = 'blue',
       main = "Visualizing Extreme Slope Residuals Accross all Individual Cases",
       xlab = "Participant ID", ylab = "Standardized Slope Residual")
  abline(h=0,lwd = 2)
  text(extremezeta1i$id, y = extremezeta1i$zeta1i/sd(id.zeta1i$zeta1i),
       labels = extremezeta1i$id, pos = 4, offset = 0.2,  cex = 0.7)


  layout(matrix(c(1,1,2,2), 2, 2, byrow = TRUE))
}

#checking fitted against actual values to see outliers and high influence points
plot(outcome,fitted(finalmodel), col = "white",
     #ylim = c(2,9), xlim = c(2,9),
     main = "Visualizing Model Fitted Values In Relation to Original Data",
     xlab = "Original Data", ylab = "Model Derived Values")
abline(lm( fitted(finalmodel)~outcome), col="blue")
text(outcome, y = fitted(finalmodel),
     labels = dataset$id, pos = 4, offset = 0,  cex = 0.7)

if (!slope) layout(matrix(c(1), 1, 1, byrow = TRUE))
#plotting fitted vs Residuals
eij<- eij [order(eij$std_eij),]
std_eijextreme <- eij[1:5,]
eij<- eij [order(eij$std_eij, decreasing = TRUE),]
std_eijextreme <- rbind(std_eijextreme,eij[1:5,])

plot (eij$fitted,eij$std_eij,  pch = 1, col = 'blue',
      main = "Visualizing Standardized Residuals In Relation to Model Derived Data",
      ylab="Standardized Residuals", xlab = "Fitted Values")
abline(h=0)
text(std_eijextreme$fitted, y = std_eijextreme$std_eij,
     labels = std_eijextreme$id, pos = 4, offset = 0.2,  cex = 0.7)


##plot predictors vs residuals: Highschool Average, SPUSS, TM, and SES.

eij <- merge(eij, dataset)

layout(matrix(c(1,1,2,2,3,3,4,5), 2, 4, byrow = TRUE))

plot(eij$SPUSS.mean, eij$eij, col = "white",ylab = "Error Residaul",
     xlab = "Centered SPUSS Mean Scores")
abline(h=0, col="blue",lwd = 2)
text(eij$SPUSS.mean, y = eij$eij,
     labels = eij$id, pos = 4, offset = 0,  cex = 0.8 )

plot(eij$TM.mean, eij$eij, col = "white", ylab = "Error Residaul",
     xlab = "Centered Time-Managemetn Mean Scores")
abline(h=0, col="blue",lwd = 2)
text(eij$TM.mean, y = eij$eij,
     labels = eij$id, pos = 4, offset = 0,  cex = 0.8)

plot(eij$ahs_avg,eij$eij, col = "white", ylab = "Error Residaul",
     xlab = "Centered High School Averages")
abline(h=0, col="blue",lwd = 2)
text(eij$ahs_avg, y = eij$eij,
     labels = eij$id, pos = 4, offset = 0,  cex = 0.8)

Boxplot(eij$eij,as.factor(eij$income), labels = eij$id, id.n = 3,  ylab = "Error Residaul",
        xlab = "Income Levels")
Boxplot(eij$eij,as.factor(eij$agender), labels = eij$id, id.n = 3,  ylab = "Error Residaul",
        xlab = "Gender (1:Female)")
mtext("Error Residuals In Relation to All Covariates and Control Variables",
      side = 3, line = -2, outer = TRUE)
```

```r
  ##Levene test for homogeneity of variance in discrete predictors


  pander(leveneTest(eij$eij,as.factor(eij$income)),
         caption = "Levene Test for Homogeneity of Residual Variance Accross Income Levels", plain.ascii = TRUE)
  pander(leveneTest(eij$eij,as.factor(eij$agender)),
         caption = "Levene Test Homogeneity of Residual Variance Accross Genders", plain.ascii = TRUE)

  #resetting layout matrix
  layout(matrix(c(1), 1, 1, byrow = TRUE))

}
#centering time varying covariates, high school average
lagdat$SPUSS.mean <- lagdat$SPUSS.mean -  mean(lagdat$SPUSS.mean)
lagdat$TM.mean <- lagdat$TM.mean -  mean(lagdat$TM.mean)
lagdat$ahs_avg <- lagdat$ahs_avg -  mean(lagdat$ahs_avg)
#Setting up recording dataset.
#OUTCOME|,  Model Num|  Model Name|Model Equation|
#Log-likelihood Ratio|AIC|BIC|Marginal R2   |Conditional R2|Comments
results<- data.frame(matrix(ncol = 10, nrow = 0))
results <-  data.frame(lapply(results, as.character), stringsAsFactors=FALSE)
colnames(results) <- x <- c("Outcome","Model Num", "Model Name","Model Equation",
                           "Log-likelihood Ratio","AIC","BIC","Marginal R2","Conditional R2","Comments")
record <-function (outcome, number, name, result, deviance, rdata, comments, df) {
  if (number == "1"){
    newrow = list(outcome, number, name,
                  paste(as.character(result$call), collapse = ' <> '),
                  'NA', round(result$AIC,1),round(result$BIC,1), 'NA', 'NA', comments)

    df<- rbind.data.frame (df, newrow, stringsAsFactors = FALSE)
    colnames(df) <- x <- c("Outcome","Model Num", "Model Name","Model Equation",
                                "Log-likelihood Ratio","AIC","BIC","Marginal R2",
                           "Conditional R2","Comments")

    return (df)
  } else {

    #Lration <.01 *, <.001 **

    lratio <- ""
    if (deviance$`p-value`[2]< 0.001) lratio <- "**"
    else if (deviance$`p-value`[2]< 0.01) lratio <- "*"

    lratio <- paste( round(deviance$L.Ratio[2],2), lratio)

    newrow = list(outcome, number, name,
                  paste(as.character(result$call), collapse = ' <> '),
                  lratio, round(result$AIC,1), round(result$BIC,1), round(rdata$Marginal,2),
                  round(rdata$Conditional,2), comments)

    df<- rbind.data.frame (df, newrow, stringsAsFactors = FALSE)
    colnames(df) <- x <- c("Outcome","Model Num", "Model Name","Model Equation",
                           "Log-likelihood Ratio","AIC","BIC","Marginal R2",
                           "Conditional R2","Comments")


    return (df)
  }
}
## Unconditional Means Model##
mod1.sacq<-lme(fixed = SACQ.mean~1, random = ~1|univ/id,
                    data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod1.sacq)
#icc - Porportion of total variablity between individuals within Univiersities
v <- VarCorr(mod1.sacq)
comments <- paste("ICC of ID in Universities =",
     round(as.numeric(v[4,1])/(as.numeric(v[2,1])+ as.numeric(v[4,1])+as.numeric(v[5,1])),2))
#record results
results<-record(outcome = "SACQ", number = "1", name = "Unconditional Means Model",
                result = summary(mod1.sacq), deviance =  "NA", rdata = "NA",
                comments = comments, df = results)
mod2.sacq<-lme(SACQ.mean ~ time, random =~time|univ/id,
                    data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2.sacq)
v2 <- VarCorr(mod2.sacq)
comments2<-paste("Proportional Reduction in individual residual when including linear growth = ",
```

```r
      round((as.numeric(v[5,1])-as.numeric(v2[7,1]) )/as.numeric(v[5,1]),2) )
#rsquared(mod2.sacq)
#pander(anova(mod1.sacq,mod2.sacq), plain.ascii = TRUE)
#record Results
results<-record(outcome = "SACQ", number = "2", name = "Unconditional  Growth Model",
                result = summary(mod2.sacq), deviance =  anova(mod1.sacq,mod2.sacq),
                rdata = rsquared(mod2.sacq),
                comments = comments2, df = results)


### Unconditional Growth Model - Quadratic ##
mod2a.sacq<-lme(SACQ.mean ~ time + I(time^2), random =~time|univ/id,
                     data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2a.sacq)
#rsquared(mod2a.sacq)
#pander(anova(mod2.sacq,mod2a.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "2a",
                name = "Unconditional Quadratic Growth Model",
                result = summary(mod2a.sacq), deviance =  anova(mod2.sacq,mod2a.sacq),
                rdata = rsquared(mod2a.sacq),
                comments = "Not an improvement.", df = results)


###3 Conditional  Model with Covariates ##
mod3.sacq<-lme(SACQ.mean ~ time + TM.mean + SPUSS.mean, random =~1|univ/id,
                    data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3.sacq)
#pander(rsquared(mod3.sacq), round = 3)
#pander(anova(mod2.sacq,mod3.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "3",
                name = "Conditional  Model with Time-Varying Covariates",
                result = summary(mod3.sacq), deviance =  anova(mod2.sacq,mod3.sacq),
                rdata = rsquared(mod3.sacq),
                comments = "Improvement over Model 2", df = results)


##3a Conditional  Model with interacting Time and Covariates ##
mod3a.sacq<-lme(SACQ.mean ~ time*SPUSS.mean*TM.mean, random =~1|univ/id,
                     data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3a.sacq)
#pander(rsquared(mod3a.sacq), round = 3)
#pander(anova(mod3.sacq,mod3a.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "3a",
                name = "Conditional  Model with Covariates Interacting with Time",
                result = summary(mod3a.sacq), deviance =  anova(mod3.sacq,mod3a.sacq),
                rdata = rsquared(mod3a.sacq),
                comments = "Not an improvement", df = results)


##4 Conditional Model with Covariates, and Controls ##
mod4.sacq<-lme(SACQ.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income,
                    random =~1|univ/id,
                    data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4.sacq)
#pander(rsquared(mod4.sacq), round = 3)
#pander(anova(mod3.sacq,mod4.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "4",
                name = "Conditional Model Including Covariates and Controls",
                result = summary(mod4.sacq), deviance =  anova(mod3.sacq,mod4.sacq),
                rdata = rsquared(mod4.sacq),
                comments = "Improvement over Model 3", df = results)



##4a Conditional with covariates and Interacting controls with time ##
mod4a.sacq<-lme(SACQ.mean ~ time  *(agender + ahs_avg + income)+ SPUSS.mean + TM.mean,
                     random =~1|univ/id,
                     data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4a.sacq)
#pander(rsquared(mod4a.sacq), round = 3)
#pander(anova(mod4.sacq,mod4a.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "4a",
                name = "Conditional Model Including covariates and Interacting Controls with Time",
                result = summary(mod4a.sacq), deviance =  anova(mod4.sacq,mod4a.sacq),
                rdata = rsquared(mod4a.sacq),
                comments = "Not an improvement", df = results)
```

```r
##4b Conditional Model with covariates interacting with controls ##
mod4b.sacq<-lme(SACQ.mean ~ time + (SPUSS.mean + TM.mean) *(agender + ahs_avg + income),
                     random =~1|univ/id,
                     data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4b.sacq)
#pander(rsquared(mod4b.sacq), round = 3)
#pander(anova(mod4.sacq,mod4b.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "4b",
                name = "Conditional Model with Covariates Interacting with Controls",
                result = summary(mod4b.sacq), deviance =  anova(mod4.sacq,mod4b.sacq),
                rdata = rsquared(mod4b.sacq),
                comments = "Not an improvement. Interaction of SPUSS and Income near significance", df = results)



##4c Conditional  Model with Covariates, Controls, and interacting Income and SPUSS ##
mod4c.sacq<-lme(SACQ.mean ~ time + SPUSS.mean*income + TM.mean + ahs_avg + agender,
                     random =~1|univ/id,
                     data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4c.sacq)
#pander(rsquared(mod4c.sacq), round = 3)
#pander(anova(mod4.sacq,mod4c.sacq), plain.ascii = TRUE)
results<-record(outcome = "SACQ", number = "4c",
                name = "Conditional Model with Covariates, Controls, Interaction between Income & SPUSS",
                result = summary(mod4c.sacq), deviance =  anova(mod4.sacq,mod4c.sacq),
                rdata = rsquared(mod4c.sacq),
                comments = "Not an improvement", df = results)


##Final SACQ Model Summmary and Details
summary(mod4.sacq)
## Linear mixed-effects model fit by maximum likelihood
##  Data: lagdat
##        AIC      BIC   logLik
##    5485.96 5542.613 -2732.98
##
## Random effects:
##  Formula: ~1 | univ
##         (Intercept)
## StdDev:    0.156299
##
##  Formula: ~1 | id %in% univ
##         (Intercept)  Residual
## StdDev:    0.617873 0.6819663
##
## Fixed effects: SACQ.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg +      income
##                  Value  Std.Error   DF  t-value p-value
## (Intercept)  5.935293 0.08887666 1196 66.78124   0e+00
## time        -0.184080 0.02148894  925 -8.56625   0e+00
## SPUSS.mean   0.345166 0.02166038  925 15.93536   0e+00
## TM.mean      0.333940 0.03427372  925  9.74333   0e+00
## agender     -0.277796 0.05022004 1196 -5.53158   0e+00
## ahs_avg      0.026587 0.00416988 1196  6.37586   0e+00
## income       0.130964 0.03523568 1196  3.71681   2e-04
##  Correlation:
##            (Intr) time   SPUSS. TM.men agendr ahs_vg
## time       -0.130
## SPUSS.mean -0.010 -0.009
## TM.mean     0.066  0.024 -0.222
## agender    -0.402 -0.021  0.053 -0.142
## ahs_avg     0.060 -0.043  0.021 -0.173 -0.016
## income     -0.519  0.004  0.000 -0.059  0.110 -0.107
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.75614573 -0.51256814  0.01548294  0.56520905  3.18064890
##
## Number of Observations: 2133
## Number of Groups:
##         univ id %in% univ
##            6         1205
intervals(mod4.sacq)
## Approximate 95% confidence intervals
##
##  Fixed effects:
##                   lower        est.       upper
## (Intercept)  5.76120821  5.93529336  6.10937850
```

```
## time        -0.22618319 -0.18407972 -0.14197624
## SPUSS.mean   0.30272649  0.34516586  0.38760524
## TM.mean      0.26678731  0.33394011  0.40109291
## agender     -0.37616354 -0.27779616 -0.17942879
## ahs_avg      0.01841892  0.02658659  0.03475425
## income       0.06194714  0.13096424  0.19998135
## attr(,"label")
## [1] "Fixed effects:"
##
##  Random Effects:
##   Level: univ
##                     lower      est.     upper
## sd((Intercept)) 0.0808866 0.156299 0.3020201
##   Level: id
##                     lower      est.     upper
## sd((Intercept)) 0.5674925 0.617873 0.6727262
##
##  Within-group standard error:
##     lower      est.     upper
## 0.6503537 0.6819663 0.7151155
pander (summary(mod4.sacq), plain.ascii = TRUE, style = 'grid', round = 3)
```

Fixed effects: SACQ.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income

	Value	Std.Error	DF	t-value	p-value
(Intercept)	5.935	0.089	1196	66.78	0
time	-0.184	0.021	925	-8.566	0
SPUSS.mean	0.345	0.022	925	15.94	0
TM.mean	0.334	0.034	925	9.743	0
agender	-0.278	0.05	1196	-5.532	0
ahs_avg	0.027	0.004	1196	6.376	0
income	0.131	0.035	1196	3.717	0

Standardized Within-Group Residuals

Min	Q1	Med	Q3	Max
-3.756	-0.5126	0.01548	0.5652	3.181

Linear mixed-effects model fit by maximum likelihood : SACQ.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income

	Observations	Groups	Log-restricted-likelihood
id	2133	1205	-2733
univ	2133	6	-2733

```
# pseudo R-square
cor(lagdat$SACQ.mean,fitted(mod4.sacq), use = "complete.obs")^2
## [1] 0.7739131
##Asumption check final model
assumptioncheck(lagdat, lagdat$SACQ.mean, mod4.sacq, slope = FALSE)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1056 rows containing non-finite values (stat_bin).
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
##Transforming CESD scores
lagdat$CESDT.mean <- sqrt(lagdat$CESD.mean)

cesdt.gg <- ggplot(lagdat, aes(CESDT.mean)) + geom_histogram(fill = "olivedrab3") +facet_wrap(~(time+1)) +
  labs(x = "CESD Root Transformed Mean Scores", y = "Frequency Count",
       title = "Distribution of Transformed CESD Mean Scores at each Longitudinal Collection Time-Point") +
  theme_light()
cesdt.gg
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1036 rows containing non-finite values (stat_bin).
## Unconditional Means Model##
mod1.cesdt<-lme(fixed = CESDT.mean~1, random = ~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod1.cesdt)
#icc - Porportion of total variablity between individuals within Univiersities
v <- VarCorr(mod1.cesdt)
comments <- paste("ICC of ID in Universities =",
                  round(as.numeric(v[4,1])/(as.numeric(v[2,1])+ as.numeric(v[4,1])+as.numeric(v[5,1])),2))
#record results
results<-record(outcome = "CESD-T", number = "1", name = "Unconditional Means Model",
                result = summary(mod1.cesdt), deviance =  "NA", rdata = "NA",
                comments = comments, df = results)
mod2.cesdt<-lme(CESDT.mean ~ time, random =~time|univ/id,
               data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2.cesdt)
v2 <- VarCorr(mod2.cesdt)
comments2<-paste("Proportional Reduction in individual residual when including linear growth = ",
                 round((as.numeric(v[5,1])-as.numeric(v2[7,1]) )/as.numeric(v[5,1]),2),"." )
#rsquared(mod2.cesdt)
#pander(anova(mod1.cesdt,mod2.cesdt), plain.ascii = TRUE)
```

```r
#record Results
results<-record(outcome = "CESD-T", number = "2", name = "Unconditional  Growth Model",
                result = summary(mod2.cesdt), deviance =  anova(mod1.cesdt,mod2.cesdt),
                rdata = rsquared(mod2.cesdt),
                comments = comments2, df = results)


### Unconditional Growth Model - Quadratic ##
mod2a.cesdt<-lme(CESDT.mean ~ time + I(time^2), random =~time|univ/id,
                data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2a.cesdt)
#rsquared(mod2a.cesdt)
#pander(anova(mod2.cesdt,mod2a.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "2a",
                name = "Unconditional Quadratic Growth Model",
                result = summary(mod2a.cesdt), deviance =  anova(mod1.cesdt,mod2a.cesdt),
                rdata = rsquared(mod2a.cesdt),
                comments = "Not an improvement.", df = results)


###3 Conditional Growth Model with Covariates##
mod3.cesdt<-lme(CESDT.mean ~ time + TM.mean + SPUSS.mean, random = ~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3.cesdt)
#pander(rsquared(mod3.cesdt), round = 3)
#pander(anova(mod2.cesdt,mod3.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "3",
                name = "Conditional Growth Model with Time-Varying Covariates",
                result = summary(mod3.cesdt), deviance =  anova(mod2.cesdt,mod3.cesdt),
                rdata = rsquared(mod3.cesdt),
                comments = "Improvement over Model 2", df = results)


##3a Conditional  Model with interacting Time and Covariates ##
mod3a.cesdt<-lme(CESDT.mean ~ time*SPUSS.mean*TM.mean, random =~1|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3a.cesdt)
#pander(rsquared(mod3a.cesdt), round = 3)
#pander(anova(mod3.cesdt,mod3a.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "3a",
                name = "Conditional Growth Model with Covariates Interacting with Time",
                result = summary(mod3a.cesdt), deviance =  anova(mod3.cesdt,mod3a.cesdt),
                rdata = rsquared(mod3a.cesdt),
                comments = "Not an improvement, and no interaction is significant",
                df = results)

##4 Conditional Growth Model with Covariates, and Controls ##
mod4.cesdt<-lme(CESDT.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income,
               random =~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4.cesdt)
#pander(rsquared(mod4.cesdt), round = 3)
#pander(anova(mod3.cesdt,mod4.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "4",
                name = "Conditional Growth Model Including Covariates and Controls",
                result = summary(mod4.cesdt), deviance =  anova(mod3.cesdt,mod4.cesdt),
                rdata = rsquared(mod4.cesdt),
                comments = "Improvement over Model 3. All control variables are significant.",
                df = results)


##4a Conditional with covariates and Interacting controls with time ##
mod4a.cesdt<-lme(CESDT.mean ~ time  *(agender + ahs_avg + income)+ SPUSS.mean + TM.mean,
                random =~1|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4a.cesdt)
#pander(rsquared(mod4a.cesdt), round = 3)
#pander(anova(mod4.cesdt,mod4a.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "4a",
                name = "Conditional Model Including covariates and Interacting Controls with Time",
                result = summary(mod4a.cesdt), deviance =  anova(mod4.cesdt,mod4a.cesdt),
                rdata = rsquared(mod4a.cesdt),
                comments = "Not an improvement. No interaction between controls and time is significant.",
                df = results)


##4b Conditional Model with covariates interacting with controls ##
```

```
mod4b.cesdt<-lme(CESDT.mean ~ time + (SPUSS.mean + TM.mean) *(agender + ahs_avg + income),
                random =~1|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4b.cesdt)
#pander(rsquared(mod4b.cesdt), round = 3)
#pander(anova(mod4.cesdt,mod4b.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "4b",
                name = "Conditional Model with Covariates Interacting with Controls",
                result = summary(mod4b.cesdt), deviance =  anova(mod4.cesdt,mod4b.cesdt),
                rdata = rsquared(mod4b.cesdt),
                comments = "Not an improvement. No interaction between covariates and controls is significant.", df = res
ults)

##4c Conditional  Model with Covariates, and Controls (excluding time) ##
mod4c.cesdt<-lme(CESDT.mean ~  SPUSS.mean + TM.mean + agender + ahs_avg + income,
                random =~1|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4c.cesdt)
#pander(rsquared(mod4c.cesdt), round = 3)
#pander(anova(mod4c.cesdt,mod4.cesdt), plain.ascii = TRUE)
results<-record(outcome = "CESD-T", number = "4",
                name = "Conditional Model Including Covariates and Controls (Excluding time)",
                result = summary(mod4c.cesdt), deviance =  anova(mod4c.cesdt,mod4.cesdt),
                rdata = rsquared(mod4c.cesdt),
                comments = "Not an improvement. A significant worse -2LL ratio.",
                df = results)


##Print Final CESD-T Model Summmary and Details
summary(mod4.cesdt)
## Linear mixed-effects model fit by maximum likelihood
##  Data: lagdat
##        AIC      BIC    logLik
##   401.5974 458.3436 -190.7987
##
## Random effects:
##  Formula: ~1 | univ
##         (Intercept)
## StdDev:  0.02734342
##
##  Formula: ~1 | id %in% univ
##         (Intercept)  Residual
## StdDev:   0.2092511 0.1960018
##
## Fixed effects: CESDT.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg +      income
##                  Value   Std.Error   DF    t-value p-value
## (Intercept)  0.8682175 0.022498103 1208   38.59070  0.0000
## time        -0.0132067 0.006248614  933   -2.11353  0.0348
## SPUSS.mean  -0.0696578 0.006599696  933  -10.55469  0.0000
## TM.mean     -0.0575372 0.010560659  933   -5.44825  0.0000
## agender      0.0829008 0.015860733 1208    5.22680  0.0000
## ahs_avg     -0.0042465 0.001307517 1208   -3.24779  0.0012
## income      -0.0438764 0.011148667 1208   -3.93557  0.0001
##  Correlation:
##            (Intr) time   SPUSS. TM.men agendr ahs_vg
## time       -0.146
## SPUSS.mean -0.008 -0.006
## TM.mean     0.078  0.027 -0.221
## agender    -0.504 -0.025  0.050 -0.136
## ahs_avg     0.075 -0.042  0.021 -0.170 -0.015
## income     -0.654  0.007 -0.007 -0.055  0.115 -0.102
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.35786899 -0.53138902 -0.01480699  0.52518841  3.38712621
##
## Number of Observations: 2153
## Number of Groups:
##         univ id %in% univ
##            6         1217
intervals(mod4.cesdt)
## Approximate 95% confidence intervals
##
##  Fixed effects:
##                    lower         est.          upper
## (Intercept)  0.824149571  0.868217455  0.9122853384
## time        -0.025449674 -0.013206659 -0.0009636439
## SPUSS.mean  -0.082588670 -0.069657774 -0.0567268779
```

```
## TM.mean     -0.078228830 -0.057537152 -0.0368454741
## agender      0.051833810  0.082900826  0.1139678418
## ahs_avg     -0.006807618 -0.004246535 -0.0016854526
## income      -0.065713677 -0.043876363 -0.0220390495
## attr(,"label")
## [1] "Fixed effects:"
##
##  Random Effects:
##   Level: univ
##                      lower       est.      upper
## sd((Intercept)) 0.01160638 0.02734342 0.06441827
##   Level: id
##                     lower      est.     upper
## sd((Intercept)) 0.1951352 0.2092511 0.2243883
##
##  Within-group standard error:
##     lower      est.     upper
## 0.1871500 0.1960018 0.2052724
pander (summary(mod4.cesdt), plain.ascii = TRUE, style = 'grid', round = 3)
```

Fixed effects: CESDT.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income

	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.868	0.022	1208	38.59	0
time	-0.013	0.006	933	-2.114	0.035
SPUSS.mean	-0.07	0.007	933	-10.55	0
TM.mean	-0.058	0.011	933	-5.448	0
agender	0.083	0.016	1208	5.227	0
ahs_avg	-0.004	0.001	1208	-3.248	0.001
income	-0.044	0.011	1208	-3.936	0

Standardized Within-Group Residuals

Min	Q1	Med	Q3	Max
-3.358	-0.5314	-0.01481	0.5252	3.387

Linear mixed-effects model fit by maximum likelihood : CESDT.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income

	Observations	Groups	Log-restricted-likelihood
id	2153	1217	-190.8
univ	2153	6	-190.8

```
# pseudo R-square
cor(lagdat$CESDT.mean,fitted(mod4.cesdt), use = "complete.obs")^2
## [1] 0.7921314
##Asumption check final model
assumptioncheck(lagdat, lagdat$CESDT.mean, mod4.cesdt, slope = FALSE)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1036 rows containing non-finite values (stat_bin).
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Unconditional Means Model##
mod1.pss<-lme(fixed = PSS.mean~1, random = ~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod1.pss)
#icc - Porportion of total variablity between individuals within Univiersities
v <- VarCorr(mod1.pss)
comments <- paste("ICC of ID in Universities =",
                  round(as.numeric(v[4,1])/(as.numeric(v[2,1])+ as.numeric(v[4,1])+as.numeric(v[5,1])),2))
#record results
results<-record(outcome = "PSS", number = "1", name = "Unconditional Means Model",
                result = summary(mod1.pss), deviance =  "NA", rdata = "NA",
                comments = comments, df = results)
mod2.pss<-lme(PSS.mean ~ time, random =~time|univ/id,
               data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2.pss)
v2 <- VarCorr(mod2.pss)
comments2<-paste("Proportional Reduction in individual residual when including linear growth = ",
                 round((as.numeric(v[5,1])-as.numeric(v2[7,1]) )/as.numeric(v[5,1]),2),
                 ". Time is not significanltly related to changes PSS" )
#rsquared(mod2.pss)
#pander(anova(mod1.pss,mod2.pss), plain.ascii = TRUE)
#record Results
results<-record(outcome = "PSS", number = "2", name = "Unconditional  Growth Model",
                result = summary(mod2.pss), deviance =  anova(mod1.pss,mod2.pss),
                rdata = rsquared(mod2.pss),
                comments = comments2, df = results)


### Unconditional Growth Model - Quadratic ##
mod2a.pss<-lme(PSS.mean ~ time + I(time^2), random =~time|univ/id,
                data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
```

```
#summary(mod2a.pss)
#rsquared(mod2a.pss)
#pander(anova(mod2.pss,mod2a.pss), plain.ascii = TRUE)
results<-record(outcome = "PSS", number = "2a",
                name = "Unconditional Quadratic Growth Model",
                result = summary(mod2a.pss), deviance =  anova(mod1.pss,mod2a.pss),
                rdata = rsquared(mod2a.pss),
                comments = "Not an improvement. Quadratic time unrelated to changes in PSS .", df = results)


###3 Conditional  Model with Covariates (Excluding Time)##
mod3.pss<-lme(PSS.mean ~ TM.mean + SPUSS.mean, random = ~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3.pss)
#pander(rsquared(mod3.pss), round = 3)
#pander(anova(mod1.pss,mod3.pss), plain.ascii = TRUE)
results<-record(outcome = "PSS", number = "3",
                name = "Conditional  Model with Time-Varying Covariates (Excluding Time)",
                result = summary(mod3.pss), deviance =  anova(mod2.pss,mod3.pss),
                rdata = rsquared(mod3.pss),
                comments = "Improvement over Model 1 (and 2)", df = results)


##3a Conditional  Model with interacting Time and Covariates ##
mod3a.pss<-lme(PSS.mean ~ time*SPUSS.mean*TM.mean, random =~time|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3a.pss)
#pander(rsquared(mod3a.pss), round = 3)
#pander(anova(mod3.pss,mod3a.pss), plain.ascii = TRUE)
results<-record(outcome = "PSS", number = "3a",
                name = "Conditional  Model with Covariates Interacting with Time",
                result = summary(mod3a.pss), deviance =  anova(mod3.pss,mod3a.pss),
                rdata = rsquared(mod3a.pss),
                comments = "Not an improvement, and no interaction is significant",
                df = results)


##4 Conditional Model with Covariates, and Controls ##
mod4.pss<-lme(PSS.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income,
               random =~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4.pss)
#pander(rsquared(mod4.pss), round = 3)
#pander(anova(mod3.pss,mod4.pss), plain.ascii = TRUE)
results<-record(outcome = "PSS", number = "4",
                name = "Conditional Model Including Covariates and Controls",
                result = summary(mod4.pss), deviance =  anova(mod3.pss,mod4.pss),
                rdata = rsquared(mod4.pss),
                comments = "Improvement over Model 3. All control variables are significant.",
                df = results)



##4a Conditional with covariates and Interacting controls with time ##
mod4a.pss<-lme(PSS.mean ~ time  *(agender + ahs_avg + income)+ SPUSS.mean + TM.mean,
                random =~time|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4a.pss)
#pander(rsquared(mod4a.pss), round = 3)
#pander(anova(mod4.pss,mod4a.pss), plain.ascii = TRUE)
results<-record(outcome = "PSS", number = "4a",
                name = "Conditional Model Including covariates and Interacting Controls with Time",
                result = summary(mod4a.pss), deviance =  anova(mod4.pss,mod4a.pss),
                rdata = rsquared(mod4a.pss),
                comments = "Not an improvement. Also no interaction is significant.",
                df = results)


##4b Conditional Model with covariates interacting with controls ##
mod4b.pss<-lme(PSS.mean ~ (SPUSS.mean + TM.mean) *(agender + ahs_avg + income),
                random =~1|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4b.pss)
#pander(rsquared(mod4b.pss), round = 3)
#pander(anova(mod4.pss,mod4b.pss), plain.ascii = TRUE)
results<-record(outcome = "PSS", number = "4b",
                name = "Conditional Model with Covariates Interacting with Controls",
```

```r
                result = summary(mod4b.pss), deviance =  anova(mod4.pss,mod4b.pss),
                rdata = rsquared(mod4b.pss),
                comments = "Not an improvement. Also no interaction is significant.", df = results)
```

```r
##Print Final PSS Model Summmary and Details
summary(mod4.pss)
## Linear mixed-effects model fit by maximum likelihood
##  Data: lagdat
##        AIC      BIC    logLik
##   4194.934 4246.006 -2088.467
##
## Random effects:
##  Formula: ~1 | univ
##         (Intercept)
## StdDev:  0.07558589
##
##  Formula: ~1 | id %in% univ
##         (Intercept)  Residual
## StdDev:   0.3953906 0.5287059
##
## Fixed effects: PSS.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income
##                   Value  Std.Error   DF    t-value p-value
## (Intercept)  1.5875536 0.05236025 1204  30.319827   0e+00
## SPUSS.mean  -0.1877242 0.01543135  938 -12.165120   0e+00
## TM.mean     -0.1704600 0.02437778  938  -6.992433   0e+00
## agender      0.1942968 0.03494743 1204   5.559688   0e+00
## ahs_avg     -0.0149746 0.00288704 1204  -5.186834   0e+00
## income      -0.0905369 0.02453448 1204  -3.690189   2e-04
##  Correlation:
##            (Intr) SPUSS. TM.men agendr ahs_vg
## SPUSS.mean -0.013
## TM.mean     0.086 -0.228
## agender    -0.478  0.054 -0.145
## ahs_avg     0.062  0.024 -0.175 -0.021
## income     -0.613 -0.002 -0.064  0.109 -0.100
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.67799844 -0.57191229 -0.03441724  0.54472795  3.88122021
##
## Number of Observations: 2153
## Number of Groups:
##         univ id %in% univ
##            6         1213
intervals(mod4.pss)
## Approximate 95% confidence intervals
##
##  Fixed effects:
##                    lower        est.        upper
## (Intercept)  1.48496938  1.58755361  1.690137836
## SPUSS.mean  -0.21796595 -0.18772421 -0.157482472
## TM.mean     -0.21823462 -0.17046002 -0.122685419
## agender      0.12582778  0.19429681  0.262765838
## ahs_avg     -0.02063091 -0.01497461 -0.009318315
## income      -0.13860483 -0.09053686 -0.042468896
## attr(,"label")
## [1] "Fixed effects:"
##
##  Random Effects:
##   Level: univ
##                       lower       est.     upper
## sd((Intercept)) 0.03529535 0.07558589 0.1618691
##   Level: id
##                      lower      est.     upper
## sd((Intercept)) 0.3602119 0.3953906 0.4340048
##
##  Within-group standard error:
##     lower      est.     upper
## 0.5061576 0.5287059 0.5522587
pander (summary(mod4.pss), plain.ascii = TRUE, style = 'grid', round = 3)
```

Fixed effects: PSS.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income

	Value	Std.Error	DF	t-value	p-value
(Intercept)	1.588	0.052	1204	30.32	0
SPUSS.mean	-0.188	0.015	938	-12.16	0
TM.mean	-0.17	0.024	938	-6.992	0

agender	0.194	0.035	1204	5.56	0
ahs_avg	-0.015	0.003	1204	-5.187	0
income	-0.091	0.025	1204	-3.69	0

Standardized Within-Group Residuals

Min	Q1	Med	Q3	Max
-2.678	-0.5719	-0.03442	0.5447	3.881

Linear mixed-effects model fit by maximum likelihood : PSS.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income

	Observations	Groups	Log-restricted-likelihood
id	2153	1213	-2088
univ	2153	6	-2088

```
# pseudo R-square
cor(lagdat$PSS.mean,fitted(mod4.pss), use = "complete.obs")^2
## [1] 0.6781701
##Asumption check final model
assumptioncheck(lagdat, lagdat$PSS.mean, mod4.pss, slope = FALSE)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Warning: Removed 1036 rows containing non-finite values (stat_bin).
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## Unconditional Means Model##
mod1.tm<-lme(fixed = TM.mean~1, random = ~1|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod1.tm)
#icc - Porportion of total variablity between individuals within Univiersities
v <- VarCorr(mod1.tm)
comments <- paste("ICC of ID in Universities =",
                  round(as.numeric(v[4,1])/(as.numeric(v[2,1])+ as.numeric(v[4,1])+as.numeric(v[5,1])),2))
#record results
results<-record(outcome = "TM", number = "1", name = "Unconditional Means Model",
                result = summary(mod1.tm), deviance =  "NA", rdata = "NA",
                comments = comments, df = results)
mod2.tm<-lme(TM.mean ~ semester, random =~semester|univ/id,
               data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2.tm)
v2 <- VarCorr(mod2.tm)
comments2<-paste("Proportional Reduction in individual residual when including linear growth = ",
                 round((as.numeric(v[5,1])-as.numeric(v2[7,1]) )/as.numeric(v[5,1]),2) )
#rsquared(mod2.tm)
#pander(anova(mod1.tm,mod2.tm), plain.ascii = TRUE)
#record Results
results<-record(outcome = "TM", number = "2", name = "Unconditional  Growth Model",
                result = summary(mod2.tm), deviance =  anova(mod1.tm,mod2.tm),
                rdata = rsquared(mod2.tm),
                comments = comments2, df = results)

###3 Conditional  Model with Covariates ##
mod3.tm<-lme(TM.mean ~ semester +  SPUSS.mean, random =~semester|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3.tm)
#pander(rsquared(mod3.tm), round = 3)
#pander(anova(mod2.tm,mod3.tm), plain.ascii = TRUE)
results<-record(outcome = "TM", number = "3",
                name = "Conditional  Model with semester-Varying Covariate",
                result = summary(mod3.tm), deviance =  anova(mod2.tm,mod3.tm),
                rdata = rsquared(mod3.tm),
                comments = "Improvement over Model 2", df = results)


##3a Conditional  Model with interacting semester and Covariate ##
mod3a.tm<-lme(TM.mean ~ semester*SPUSS.mean, random =~semester|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3a.tm)
#pander(rsquared(mod3a.tm), round = 3)
#pander(anova(mod3.tm,mod3a.tm), plain.ascii = TRUE)
results<-record(outcome = "TM", number = "3a",
                name = "Conditional  Model with Covariates Interacting with semester",
                result = summary(mod3a.tm), deviance =  anova(mod3.tm,mod3a.tm),
                rdata = rsquared(mod3a.tm),
                comments = "Not an improvement", df = results)


##4 Conditional Model with Covariates, and Controls ##
mod4.tm<-lme(TM.mean ~ semester + SPUSS.mean + agender + ahs_avg + income,
               random =~semester|univ/id,
               data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4.tm)
#pander(rsquared(mod4.tm), round = 3)
```

```
#pander(anova(mod3.tm,mod4.tm), plain.ascii = TRUE)
results<-record(outcome = "TM", number = "4",
                name = "Conditional Model Including Covariate and Controls",
                result = summary(mod4.tm), deviance =  anova(mod3.tm,mod4.tm),
                rdata = rsquared(mod4.tm),
                comments = "Improvement over Model 3", df = results)



##4a Conditional with covariates and Interacting controls with semester ##
mod4a.tm<-lme(TM.mean ~ semester  *(agender + ahs_avg + income) + SPUSS.mean,
                random =~semester|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4a.tm)
#pander(rsquared(mod4a.tm), round = 3)
#pander(anova(mod4.tm,mod4a.tm), plain.ascii = TRUE)
results<-record(outcome = "TM", number = "4a",
                name = "Conditional Model Including covariates and Interacting Controls with semester",
                result = summary(mod4a.tm), deviance =  anova(mod4.tm,mod4a.tm),
                rdata = rsquared(mod4a.tm),
                comments = "Not an improvement, however interaction of Semester and Gender is significant", df = results)


##4b Conditional Model with covariates interacting with controls ##
mod4b.tm<-lme(TM.mean ~ semester + SPUSS.mean *(agender + ahs_avg + income),
                random =~semester|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4b.tm)
#pander(rsquared(mod4b.tm), round = 3)
#pander(anova(mod4.tm,mod4b.tm), plain.ascii = TRUE)
results<-record(outcome = "TM", number = "4b",
                name = "Conditional Model with Covariates Interacting with Controls",
                result = summary(mod4b.tm), deviance =  anova(mod4.tm,mod4b.tm),
                rdata = rsquared(mod4b.tm),
                comments = "Not an improvement. ", df = results)



##4c Conditional  Model with Covariates and two Controls ##
mod4c.tm<-lme(TM.mean ~ SPUSS.mean + ahs_avg + income + agender*semester,
                random =~semester|univ/id,
                data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4c.tm)
#pander(rsquared(mod4c.tm), round = 3)
#pander(anova(mod4.tm,mod4c.tm), plain.ascii = TRUE)
results<-record(outcome = "TM", number = "4c",
                name = "Conditional Model with Covariates,Controls, and Interaction between Gender & Semester",
                result = summary(mod4c.tm), deviance =  anova(mod4.tm,mod4c.tm),
                rdata = rsquared(mod4c.tm),
                comments = "Improvement over model 4", df = results)


##Print Final TM Model Summary and Details
summary(mod4c.tm)
## Linear mixed-effects model fit by maximum likelihood
##  Data: lagdat
##        AIC      BIC    logLik
##   4666.992 4751.936 -2319.496
##
## Random effects:
##  Formula: ~semester | univ
##  Structure: General positive-definite, Log-Cholesky parametrization
##             StdDev      Corr
## (Intercept) 0.021807151 (Intr)
## semester    0.004969986 -0.251
##
##  Formula: ~semester | id %in% univ
##  Structure: General positive-definite, Log-Cholesky parametrization
##             StdDev     Corr
## (Intercept) 0.58023514 (Intr)
## semester    0.07328129 -0.15
## Residual    0.29138902
##
## Fixed effects: TM.mean ~ SPUSS.mean + ahs_avg + income + agender * semester
##                          Value  Std.Error   DF   t-value p-value
## (Intercept)      -0.14008372 0.04328927 1791 -3.235991  0.0012
## SPUSS.mean        0.11073114 0.01023297 1791 10.821021  0.0000
```

```
## ahs_avg           0.02050461 0.00278114 1386  7.372728  0.0000
## income            0.03998618 0.02426836 1386  1.647667  0.0996
## agender           0.16547088 0.03537153 1386  4.678081  0.0000
## semester         -0.03072691 0.00766875 1791 -4.006771  0.0001
## agender:semester  0.02853612 0.00938276 1791  3.041336  0.0024
##  Correlation:
##                  (Intr) SPUSS. ahs_vg income agendr semstr
## SPUSS.mean        0.004
## ahs_avg           0.091 -0.012
## income           -0.740 -0.020 -0.116
## agender          -0.575  0.024 -0.005  0.101
## semester         -0.195  0.029 -0.004  0.006  0.217
## agender:semester  0.147 -0.023 -0.003 -0.004 -0.286 -0.757
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.19744468 -0.44028673  0.01987787  0.44534031  3.11409685
##
## Number of Observations: 3189
## Number of Groups:
##         univ id %in% univ
##            6         1395
intervals(mod4c.tm)
## Approximate 95% confidence intervals
##
##  Fixed effects:
##                        lower        est.       upper
## (Intercept)      -0.22489328 -0.14008372 -0.05527416
## SPUSS.mean        0.09068337  0.11073114  0.13077891
## ahs_avg           0.01505489  0.02050461  0.02595432
## income           -0.00756822  0.03998618  0.08754058
## agender           0.09615956  0.16547088  0.23478220
## semester         -0.04575103 -0.03072691 -0.01570280
## agender:semester  0.01015402  0.02853612  0.04691822
## attr(,"label")
## [1] "Fixed effects:"
##
##  Random Effects:
##   Level: univ
##                                  lower         est.     upper
## sd((Intercept))            0.0018955305  0.021807151 0.2508806
## sd(semester)               0.0004412789  0.004969986 0.0559754
## cor((Intercept),semester) -0.9527934212 -0.250631007 0.8738335
##   Level: id
##                                lower        est.       upper
## sd((Intercept))            0.55519585  0.58023514  0.60640370
## sd(semester)               0.06145188  0.07328129  0.08738786
## cor((Intercept),semester) -0.24901529 -0.14993342 -0.04774559
##
##  Within-group standard error:
##     lower      est.     upper
## 0.2788957 0.2913890 0.3044420
pander (summary(mod4c.tm), plain.ascii = TRUE, style = 'grid', round = 3)
```

Fixed effects: TM.mean ~ SPUSS.mean + ahs_avg + income + agender * semester

	Value	Std.Error	DF	t-value	p-value
(Intercept)	-0.14	0.043	1791	-3.236	0.001
SPUSS.mean	0.111	0.01	1791	10.82	0
ahs_avg	0.021	0.003	1386	7.373	0
income	0.04	0.024	1386	1.648	0.1
agender	0.165	0.035	1386	4.678	0
semester	-0.031	0.008	1791	-4.007	0
agender:semester	0.029	0.009	1791	3.041	0.002

Standardized Within-Group Residuals

Min	Q1	Med	Q3	Max
-3.197	-0.4403	0.01988	0.4453	3.114

Linear mixed-effects model fit by maximum likelihood : TM.mean ~ SPUSS.mean + ahs_avg + income + agender * semester

	Observations	Groups	Log-restricted-likelihood
id	3189	1395	-2319
univ	3189	6	-2319

```
# pseudo R-square
cor(lagdat$TM.mean,fitted(mod4c.tm), use = "complete.obs")^2
## [1] 0.9140117
##Asumption check final model
assumptioncheck(lagdat, lagdat$TM.mean, mod4c.tm)
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

## Unconditional Means Model##
mod1.spuss<-lme(fixed = SPUSS.mean~1, random = ~1|univ/id,
             data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod1.spuss)
#icc - Porportion of total variablity between individuals within Univiersities
v <- VarCorr(mod1.spuss)
comments <- paste("ICC of ID in Universities =",
                  round(as.numeric(v[4,1])/(as.numeric(v[2,1])+ as.numeric(v[4,1])+as.numeric(v[5,1])),2))
#record results
results<-record(outcome = "SPUSS", number = "1", name = "Unconditional Means Model",
                result = summary(mod1.spuss), deviance =  "NA", rdata = "NA",
                comments = comments, df = results)
mod2.spuss<-lme(SPUSS.mean ~ semester, random =~semester|univ/id,
             data=lagdat,method="ML", na.action='na.exclude', control=ctrl)
#summary(mod2.spuss)
v2 <- VarCorr(mod2.spuss)
comments2<-paste("Proportional Reduction in individual residual when including linear growth = ",
                 round((as.numeric(v[5,1])-as.numeric(v2[7,1]) )/as.numeric(v[5,1]),2),
                 "Semester is not a significant predictor of SPUSS" )
#rsquared(mod2.spuss)
#pander(anova(mod1.spuss,mod2.spuss), plain.ascii = TRUE)
#record Results
results<-record(outcome = "SPUSS", number = "2", name = "Unconditional  Growth Model",
                result = summary(mod2.spuss), deviance =  anova(mod1.spuss,mod2.spuss),
                rdata = rsquared(mod2.spuss),
                comments = comments2, df = results)

###3 Conditional  Model with Covariates ##
mod3.spuss<-lme(SPUSS.mean ~ TM.mean, random =~1|univ/id,
             data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3.spuss)
#pander(rsquared(mod3.spuss), round = 3)
#pander(anova(mod2.spuss,mod3.spuss), plain.ascii = TRUE)
results<-record(outcome = "SPUSS", number = "3",
                name = "Conditional  Model with semester-Varying Covariate",
                result = summary(mod3.spuss), deviance =  anova(mod2.spuss,mod3.spuss),
                rdata = rsquared(mod3.spuss),
                comments = "Improvement over Model 2", df = results)

##3a Conditional  Model with interacting semester and Covariate ##
mod3a.spuss<-lme(SPUSS.mean ~ semester*TM.mean, random =~1|univ/id,
              data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod3a.spuss)
#pander(rsquared(mod3a.spuss), round = 3)
#pander(anova(mod3.spuss,mod3a.spuss), plain.ascii = TRUE)
results<-record(outcome = "SPUSS", number = "3a",
                name = "Conditional  Model with Covariate Interacting with semester",
                result = summary(mod3a.spuss), deviance =  anova(mod3.spuss,mod3a.spuss),
                rdata = rsquared(mod3a.spuss),
                comments = "Not an improvement and no interaction is significant",
                df = results)

##4 Conditional Model with Covariates, and Controls ##
mod4.spuss<-lme(SPUSS.mean ~ TM.mean + agender + ahs_avg + income,
             random =~1|univ/id,
             data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4.spuss)
#pander(rsquared(mod4.spuss), round = 3)
#pander(anova(mod3.spuss,mod4.spuss), plain.ascii = TRUE)
results<-record(outcome = "SPUSS", number = "4",
                name = "Conditional Model Including Covariate and Controls",
                result = summary(mod4.spuss), deviance =  anova(mod3.spuss,mod4.spuss),
                rdata = rsquared(mod4.spuss),
                comments = "Not an improvement, however Gender is a significant control",
                df = results)

##4a Conditional with covariates and Interacting controls with semester ##
mod4a.spuss<-lme(SPUSS.mean ~ semester  *(agender + ahs_avg + income)+ TM.mean,
              random =~1|univ/id,
              data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4a.spuss)
#pander(rsquared(mod4a.spuss), round = 3)
#pander(anova(mod3.spuss,mod4a.spuss), plain.ascii = TRUE)
results<-record(outcome = "SPUSS", number = "4a",
```

```
                name = "Conditional Model Including covariates and Interacting Controls with semester",
                result = summary(mod4a.spuss), deviance =  anova(mod3.spuss,mod4a.spuss),
                rdata = rsquared(mod4a.spuss),
                comments = "Improvement over model 3. Interaction between income and semester is significant", df = resul
ts)

##4b Conditional Model with covariate interacting with controls ##
mod4b.spuss<-lme(SPUSS.mean ~ semester + TM.mean *(agender + ahs_avg + income),
              random =~1|univ/id,
              data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4b.spuss)
#pander(rsquared(mod4b.spuss), round = 3)
#pander(anova(mod4.spuss,mod4b.spuss), plain.ascii = TRUE)
results<-record(outcome = "SPUSS", number = "4b",
                name = "Conditional Model with Covariates Interacting with Controls",
                result = summary(mod4b.spuss), deviance =  anova(mod4.spuss,mod4b.spuss),
                rdata = rsquared(mod4b.spuss),
                comments = "Not an improvement. ", df = results)

##4c Conditional  Model with Covariates and two Controls, and ##
mod4c.spuss<-lme(SPUSS.mean ~ TM.mean + agender + semester*income,
              random =~1|univ/id,
              data=lagdat,method="ML", na.action='na.exclude',control=ctrl)
#summary(mod4c.spuss)
#pander(rsquared(mod4c.spuss), round = 3)
#pander(anova(mod3.spuss,mod4c.spuss), plain.ascii = TRUE)
results<-record(outcome = "SPUSS", number = "4c",
                name = "Conditional Model with Covariate, Two Controls, and Interaction between Income & time",
                result = summary(mod4c.spuss), deviance =  anova(mod3.spuss,mod4c.spuss),
                rdata = rsquared(mod4c.spuss),
                comments = "Improvement over Model 3. More parsimonious than model 4a without being a worse fit.", df = r
esults)

##Pring Final SPUSS Model Summmary and Details
summary(mod4c.spuss)
## Linear mixed-effects model fit by maximum likelihood
##  Data: lagdat
##        AIC      BIC    logLik
##   7926.479 7981.086 -3954.239
##
## Random effects:
##  Formula: ~1 | univ
##         (Intercept)
## StdDev:   0.2382406
##
##  Formula: ~1 | id %in% univ
##         (Intercept)  Residual
## StdDev:   0.8198219 0.5752453
##
## Fixed effects: SPUSS.mean ~ TM.mean + agender + semester * income
##                      Value  Std.Error   DF   t-value p-value
## (Intercept)      0.0103214 0.11693929 1791  0.088263  0.9297
## TM.mean          0.3369555 0.02819773 1791 11.949740  0.0000
## agender         -0.1426187 0.05102365 1387 -2.795149  0.0053
## semester         0.0266169 0.01469785 1791  1.810940  0.0703
## income           0.0315855 0.03831913 1387  0.824275  0.4099
## semester:income -0.0247786 0.01048474 1791 -2.363304  0.0082
##  Correlation:
##                 (Intr) TM.men agendr semstr income
## TM.mean          0.052
## agender         -0.313 -0.108
## semester        -0.155 -0.007  0.007
## income          -0.429 -0.061  0.108  0.291
## semester:income  0.137  0.032 -0.010 -0.868 -0.332
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -3.70611788 -0.50652821  0.01310317  0.50411532  3.62507205
##
## Number of Observations: 3189
## Number of Groups:
##         univ id %in% univ
##            6         1395
intervals(mod4c.spuss)
## Approximate 95% confidence intervals
##
##  Fixed effects:
##                        lower        est.       upper
```

```
## (Intercept)     -0.218814545  0.01032138  0.23945730
## TM.mean          0.281703668  0.33695552  0.39220737
## agender         -0.242616357 -0.14261869 -0.04262103
## semester        -0.002182683  0.02661692  0.05541653
## income          -0.043513438  0.03158552  0.10668447
## semester:income -0.045322866 -0.02477862 -0.00423437
## attr(,"label")
## [1] "Fixed effects:"
##
##  Random Effects:
##   Level: univ
##                     lower      est.     upper
## sd((Intercept)) 0.1306037 0.2382406 0.4345861
##   Level: id
##                    lower      est.     upper
## sd((Intercept)) 0.782938 0.8198219 0.8584434
##
##  Within-group standard error:
##     lower      est.     upper
## 0.5567918 0.5752453 0.5943105
pander (summary(mod4c.spuss), plain.ascii = TRUE, style = 'grid', round = 3)
```

Fixed effects: SPUSS.mean ~ TM.mean + agender + semester * income

	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.01	0.117	1791	0.088	0.93
TM.mean	0.337	0.028	1791	11.95	0
agender	-0.143	0.051	1387	-2.795	0.005
semester	0.027	0.015	1791	1.811	0.07
income	0.032	0.038	1387	0.824	0.41
semester:income	-0.025	0.01	1791	-2.363	0.008

Standardized Within-Group Residuals

Min	Q1	Med	Q3	Max
-3.706	-0.5065	0.0131	0.5041	3.625

Linear mixed-effects model fit by maximum likelihood : SPUSS.mean ~ TM.mean + agender + semester * income

	Observations	Groups	Log-restricted-likelihood
id	3189	1395	-3954
univ	3189	6	-3954

```
# pseudo R-square
cor(lagdat$SPUSS.mean,fitted(mod4c.spuss), use = "complete.obs")^2
## [1] 0.8284651
##Asumption check final model
assumptioncheck(lagdat, lagdat$SPUSS.mean, mod4c.spuss, slope = FALSE)
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
pander(results)
```

Table continues below

Outcome	Model Num	Model Name
SACQ	1	Unconditional Means Model
SACQ	2	Unconditional Growth Model
SACQ	2a	Unconditional Quadratic Growth Model
SACQ	3	Conditional Model with Time-Varying Covariates
SACQ	3a	Conditional Model with Covariates Interacting with Time
SACQ	4	Conditional Model Including Covariates and Controls
SACQ	4a	Conditional Model Including covariates and Interacting Controls with Time
SACQ	4b	Conditional Model with Covariates Interacting with Controls
SACQ	4c	Conditional Model with Covariates, Controls, Interaction between Income & SPUSS
CESD-T	1	Unconditional Means Model
CESD-T	2	Unconditional Growth Model
CESD-T	2a	Unconditional Quadratic Growth Model
CESD-T	3	Conditional Growth Model with Time-Varying Covariates
CESD-T	3a	Conditional Growth Model with Covariates Interacting with Time
CESD-T	4	Conditional Growth Model Including Covariates and Controls
CESD-T	4a	Conditional Model Including covariates and Interacting Controls with Time
CESD-T	4b	Conditional Model with Covariates Interacting with Controls
CESD-T	4	Conditional Model Including Covariates and Controls (Excluding time)
PSS	1	Unconditional Means Model
PSS	2	Unconditional Growth Model
PSS	2a	Unconditional Quadratic Growth Model
PSS	3	Conditional Model with Time-Varying Covariates (Excluding Time)
PSS	3a	Conditional Model with Covariates Interacting with Time
PSS	4	Conditional Model Including Covariates and Controls
PSS	4a	Conditional Model Including covariates and Interacting Controls with Time
PSS	4b	Conditional Model with Covariates Interacting with Controls
TM	1	Unconditional Means Model
TM	2	Unconditional Growth Model

TM	3	Conditional Model with semester-Varying Covariate
TM	3a	Conditional Model with Covariates Interacting with semester
TM	4	Conditional Model Including Covariate and Controls
TM	4a	Conditional Model Including covariates and Interacting Controls with semester
TM	4b	Conditional Model with Covariates Interacting with Controls
TM	4c	Conditional Model with Covariates,Controls, and Interaction between Gender & Semester
SPUSS	1	Unconditional Means Model
SPUSS	2	Unconditional Growth Model
SPUSS	3	Conditional Model with semester-Varying Covariate
SPUSS	3a	Conditional Model with Covariate Interacting with semester
SPUSS	4	Conditional Model Including Covariate and Controls
SPUSS	4a	Conditional Model Including covariates and Interacting Controls with semester
SPUSS	4b	Conditional Model with Covariates Interacting with Controls
SPUSS	4c	Conditional Model with Covariate, Two Controls, and Interaction between Income & time

Table continues below

Model Equation	Log-likelihood Ratio	AIC	BIC
lme.formula <> SACQ.mean ~ 1 <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	NA	5964	5986
lme.formula <> SACQ.mean ~ time <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	92.34 **	5882	5932
lme.formula <> SACQ.mean ~ time + I(time^2) <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	0.46	5883	5940
lme.formula <> SACQ.mean ~ time + TM.mean + SPUSS.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	304.73 **	5573	5612
lme.formula <> SACQ.mean ~ time * SPUSS.mean * TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	11.37	5569	5632
lme.formula <> SACQ.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	92.85 **	5486	5543
lme.formula <> SACQ.mean ~ time * (agender + ahs_avg + income) + SPUSS.mean + TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	3.98	5488	5562
lme.formula <> SACQ.mean ~ time + (SPUSS.mean + TM.mean) * (agender + ahs_avg + income) <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	11.08	5487	5578
lme.formula <> SACQ.mean ~ time + SPUSS.mean * income + TM.mean + ahs_avg + agender <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	4.83	5483	5545
lme.formula <> CESDT.mean ~ 1 <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	NA	604	626.7
lme.formula <> CESDT.mean ~ time <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	16.69 *	597.3	648.4
lme.formula <> CESDT.mean ~ time + I(time^2) <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	20.97 *	595	651.8
lme.formula <> CESDT.mean ~ time + TM.mean + SPUSS.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	137.4 **	455.9	495.6
lme.formula <> CESDT.mean ~ time * SPUSS.mean * TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	8.25	455.6	518.1
lme.formula <> CESDT.mean ~ time + SPUSS.mean + TM.mean + agender + ahs_avg + income <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	60.3 **	401.6	458.3
lme.formula <> CESDT.mean ~ time * (agender + ahs_avg + income) + SPUSS.mean + TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	1.41	406.2	480
lme.formula <> CESDT.mean ~ time + (SPUSS.mean + TM.mean) * (agender + ahs_avg + income) <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	5.45	408.1	498.9
lme.formula <> CESDT.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	4.48	404.1	455.1
lme.formula <> PSS.mean ~ 1 <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	NA	4476	4498
lme.formula <> PSS.mean ~ time <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	4.61	4481	4532
lme.formula <> PSS.mean ~ time + I(time^2) <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	10.78	4477	4533
lme.formula <> PSS.mean ~ TM.mean + SPUSS.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	207.96 **	4267	4301
lme.formula <> PSS.mean ~ time * SPUSS.mean * TM.mean <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	10.45	4274	4360
lme.formula <> PSS.mean ~ SPUSS.mean + TM.mean + agender + ahs_avg + income <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	77.95 **	4195	4246
lme.formula <> PSS.mean ~ time * (agender + ahs_avg + income) + SPUSS.mean + TM.mean <> lagdat <> ~time | univ/id <> ML <> na.exclude <> ctrl	8.21	4203	4299
lme.formula <> PSS.mean ~ (SPUSS.mean + TM.mean) * (agender + ahs_avg + income) <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	8.51	4198	4284
lme.formula <> TM.mean ~ 1 <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	NA	4922	4946
lme.formula <> TM.mean ~ semester <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	66.33 **	4866	4920
lme.formula <> TM.mean ~ semester + SPUSS.mean <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	110.41 **	4757	4818
lme.formula <> TM.mean ~ semester * SPUSS.mean <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	3.4	4756	4823
lme.formula <> TM.mean ~ semester + SPUSS.mean + agender + ahs_avg + income <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	89.25 **	4674	4753
lme.formula <> TM.mean ~ semester * (agender + ahs_avg + income) + SPUSS.mean <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	10.22	4670	4767
lme.formula <> TM.mean ~ semester + SPUSS.mean * (agender + ahs_avg + income) <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	3.72	4676	4773
lme.formula <> TM.mean ~ SPUSS.mean + ahs_avg + income + agender * semester <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	9.08 *	4667	4752
lme.formula <> SPUSS.mean ~ 1 <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	NA	8067	8091
lme.formula <> SPUSS.mean ~ semester <> lagdat <> ~semester | univ/id <> ML <> na.exclude <> ctrl	18.63 *	8058	8113
lme.formula <> SPUSS.mean ~ TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	118.03 **	7932	7963
lme.formula <> SPUSS.mean ~ semester * TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	1.1	7935	7978

lme.formula <> SPUSS.mean ~ TM.mean + agender + ahs_avg + income <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	8.19	7930	7979
lme.formula <> SPUSS.mean ~ semester * (agender + ahs_avg + income) + TM.mean <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	14.56	7932	8005
lme.formula <> SPUSS.mean ~ semester + TM.mean * (agender + ahs_avg + income) <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	2.29	7936	8009
lme.formula <> SPUSS.mean ~ TM.mean + agender + semester * income <> lagdat <> ~1 | univ/id <> ML <> na.exclude <> ctrl	13.88 *	7926	7981

Marginal R2	Conditional R2	Comments
NA	NA	ICC of ID in Universities = 0.63
0.02	0.7	Proportional Reduction in individual residual when including linear growth = 0.11
0.02	0.7	Not an improvement.
0.21	0.6	Improvement over Model 2
0.2	0.6	Not an improvement
0.27	0.61	Improvement over Model 3
0.26	0.61	Not an improvement
0.27	0.61	Not an improvement. Interaction of SPUSS and Income near significance
0.27	0.61	Not an improvement
NA	NA	ICC of ID in Universities = 0.62
0	0.73	Proportional Reduction in individual residual when including linear growth = 0.17 .
0	0.73	Not an improvement.
0.09	0.59	Improvement over Model 2
0.09	0.6	Not an improvement, and no interaction is significant
0.13	0.6	Improvement over Model 3. All control variables are significant.
0.13	0.6	Not an improvement. No interaction between controls and time is significant.
0.13	0.6	Not an improvement. No interaction between covariates and controls is significant.
0.13	0.6	Not an improvement. A significant worse -2LL ratio.
NA	NA	ICC of ID in Universities = 0.49
0	0.52	Proportional Reduction in individual residual when including linear growth = 0.02 . Time is not significanltly related to changes PSS
0	0.53	Not an improvement. Quadratic time unrelated to changes in PSS .
0.13	0.47	Improvement over Model 1 (and 2)
0.12	0.45	Not an improvement, and no interaction is significant
0.17	0.47	Improvement over Model 3. All control variables are significant.
0.18	0.46	Not an improvement. Also no interaction is significant.
0.18	0.48	Not an improvement. Also no interaction is significant.
NA	NA	ICC of ID in Universities = 0.77
0	0.83	Proportional Reduction in individual residual when including linear growth = 0.22
0.03	0.82	Improvement over Model 2
0.03	0.82	Not an improvement
0.08	0.82	Improvement over Model 3
0.08	0.82	Not an improvement, however interaction of Semester and Gender is significant
0.08	0.82	Not an improvement.
0.08	0.82	Improvement over model 4
NA	NA	ICC of ID in Universities = 0.65
0	0.72	Proportional Reduction in individual residual when including linear growth = 0.08 Semester is not a significant predictor of SPUSS
0.05	0.7	Improvement over Model 2
0.05	0.7	Not an improvement and no interaction is significant
0.05	0.7	Not an improvement, however Gender is a significant control
0.05	0.7	Improvement over model 3. Interaction between income and semester is significant
0.05	0.7	Not an improvement.
0.05	0.7	Improvement over Model 3. More parsimonious than model 4a without being a worse fit.

```
##setting up SPUSS, TM Means and SDs accross time points.
SPUSS <- c(mean(lagdat$SPUSS.mean[lagdat$time==0], na.rm = TRUE),
           mean(lagdat$SPUSS.mean[lagdat$time==1], na.rm = TRUE),
           mean(lagdat$SPUSS.mean[lagdat$time==2], na.rm = TRUE))
TM <- c(mean(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE),
           mean(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
           mean(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE))
SPUSSlow <- c(mean(lagdat$SPUSS.mean[lagdat$time==0], na.rm = TRUE) -
                sd(lagdat$SPUSS.mean[lagdat$time==0], na.rm = TRUE),
           mean(lagdat$SPUSS.mean[lagdat$time==1], na.rm = TRUE)-
             sd(lagdat$SPUSS.mean[lagdat$time==1], na.rm = TRUE),
           mean(lagdat$SPUSS.mean[lagdat$time==2], na.rm = TRUE)-
             sd(lagdat$SPUSS.mean[lagdat$time==2], na.rm = TRUE))
SPUSShigh <- c(mean(lagdat$SPUSS.mean[lagdat$time==0], na.rm = TRUE) +
                sd(lagdat$SPUSS.mean[lagdat$time==0], na.rm = TRUE),
              mean(lagdat$SPUSS.mean[lagdat$time==1], na.rm = TRUE)+
                sd(lagdat$SPUSS.mean[lagdat$time==1], na.rm = TRUE),
              mean(lagdat$SPUSS.mean[lagdat$time==2], na.rm = TRUE)+
                sd(lagdat$SPUSS.mean[lagdat$time==2], na.rm = TRUE))
TMlow <- c(mean(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE) -
                sd(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE),
              mean(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE)-
                sd(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
```

```
              mean(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE)-
                sd(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE))
TMhigh <- c(mean(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE) +
                 sd(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE),
               mean(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE)+
                 sd(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
               mean(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE)+
                 sd(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE))
GENDER <- c(0,1)
SES <- c(0,1,2,3)
## For High school GPA level 1 is 1SD below mean, level 2 is mean, level 3 is 1SD above
GPA <-c(mean(lagdat$ahs_avg)-sd(lagdat$ahs_avg),mean(lagdat$ahs_avg),
        mean(lagdat$ahs_avg)+sd(lagdat$ahs_avg))
GPA<- round(GPA,3)

#### SACQ Model Equations and Plot of Trajectories : ----
ef.sacq <- fixef (mod4.sacq)

#line for Male - Average GPA and average SES
fun.sacq.m <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.f <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
#line for Low/high GPA Female - Average SES
fun.sacq.lgpaf <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[1] + ef.sacq[7]*SES[2]}
fun.sacq.hgpaf <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[3] + ef.sacq[7]*SES[2]}
fun.sacq.lgpam <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[1] + ef.sacq[7]*SES[2]}
fun.sacq.hgpam <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[3] + ef.sacq[7]*SES[2]}
#line for Low SES and High SES
fun.sacq.fses1 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[1]}
fun.sacq.fses2 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.fses3 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[3]}
fun.sacq.fses4 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[4]}
fun.sacq.mses1 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[1]}
fun.sacq.mses2 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.mses3 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[3]}
fun.sacq.mses4 <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[4]}
#high demo versus lowest demo
fun.sacq.hdemo <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[3] + ef.sacq[7]*SES[4]}
fun.sacq.ldemo <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[1] + ef.sacq[7]*SES[1]}
##SPUSS
fun.sacq.hspussm <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSShigh[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.lspussm <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSSlow[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.hspussf <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSShigh[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.lspussf <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSSlow[x+1] +
    ef.sacq[4]* TM[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
##TM
fun.sacq.htmm <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TMhigh[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.ltmm <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TMlow[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.htmf <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TMhigh[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.ltmf <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSS[x+1] +
    ef.sacq[4]* TMlow[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}

##hypothesis 5 b/c/d : lowTM high spuss, Low SPUSS high TM, Low and Low.
fun.sacq.lowtmhighspuss <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSShigh[x+1] +
    ef.sacq[4]* TMlow[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
fun.sacq.lowspusshightm <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSSlow[x+1] +
    ef.sacq[4]* TMhigh[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}
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fun.sacq.low <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSSlow[x+1] +
    ef.sacq[4]* TMlow[x+1] + ef.sacq[5]*GENDER[1] + ef.sacq[6]*GPA[2] + ef.sacq[7]*SES[2]}

##SACQ Hypothesis 5 plots - comparing low/high SPUSS/TM
plot.sacq.5 <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5),
                aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.lowtmhighspuss , n = 3, show.legend = TRUE, aes(colour = "blue1"),
                size = 1.5) +
  stat_function(fun = fun.sacq.lowspusshightm , n = 3, show.legend = TRUE, aes(colour = "green1"),
                size = 1.5) +
  stat_function(fun = fun.sacq.low , n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green1'='green1','blue1'='blue1',
              'red'='red'),
    labels = c('Overall Average','High SPUSS and Low TM','High TM and Low SPUSS',
               'Low on both SPUSS and TM')) +
  ggtitle("Adjustment Trajectories of Students with Varied \nSPUSS and TM Levels Given Average Covariates")

## Gender SACQ plot
plot.sacq.gender <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.m, n = 3, show.legend = TRUE, aes(colour = "red3"),
                size = 1.5) +
  stat_function(fun = fun.sacq.f, n = 3, show.legend = TRUE, aes(colour = "blue3"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red3'='red3','blue3'='blue3' ),
    labels = c('Overall Average','Female Students','Male Students')) +
  ggtitle("Male and Female Adjustment Trajectories Given Average Covariates")

##HGPA SACQ plot
plot.sacq.hgpa <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.lgpaf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.sacq.hgpaf, n = 3, show.legend = TRUE, aes(colour = "blue1"),
                size = 1.5) +
  stat_function(fun = fun.sacq.lgpam, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  stat_function(fun = fun.sacq.hgpam, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red4'='red4','red'='red','blue4'='blue4','blue1'='blue1' ),
    labels = c('Overall Average',"Female High HGPA","Female Low HGPA",'Male High HGPA', 'Male Low HGPA')) +
  ggtitle("Adjustment Trajectories of Students Depending on \nHigh School GPA Given Average Covariates")

##SACQ SES Plot
plot.sacq.ses <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5),
                aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.fses1 , n = 3, show.legend = TRUE, aes(colour = "green4"),
                size = 1.5) +
  stat_function(fun = fun.sacq.fses4 , n = 3, show.legend = TRUE, aes(colour = "green1"),
                size = 1.5) +
  stat_function(fun = fun.sacq.mses1 , n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  stat_function(fun = fun.sacq.mses4 , n = 3, show.legend = TRUE, aes(colour = "red1"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
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  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green1'='green1','green4'='green4',
              'red1'='red1','red4'='red4'),
    labels = c('Overall Average','Female Student Very High SES','Female Student Low SES',
               'Male Student Very High SES','Male Student Low SES')) +
  ggtitle("Adjustment Trajectories of Students Depending on Perceived \nSocio-Economic Status Given Average Covariates")

## High Low Demo SACQ Contrast
plot.sacq.demo <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.hdemo, n = 3, show.legend = TRUE, aes(colour = "green3"),
                size = 1.5) +
  stat_function(fun = fun.sacq.ldemo, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green3'='green3','red4'='red4' ),
    labels = c('Overall Average','High SES Male with High HGPA',
               'Low SES Female with Low HGPA')) +
  ggtitle("Contrasting Trajectories of Students with High and Low \nAdvantages Given Average Covariates")

##SPUSS
plot.sacq.spuss <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.hspussf, n = 3, show.legend = TRUE, aes(colour = "blue"),
                size = 1.5) +
  stat_function(fun = fun.sacq.lspussf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.sacq.hspussm, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  stat_function(fun = fun.sacq.lspussm, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red'='red','red4'='red4','blue'='blue','blue4'='blue4' ),
    labels = c('Overall Average','Female Student High SPUSS','Female Student Low SPUSS',
               'Male Student High SPUSS', 'Male Student Low SPUSS')) +
  ggtitle("Male and Female Adjustment Trajectories Depending on SPUSS \nGiven Average Covariates")

##TM
plot.sacq.tm <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.htmf, n = 3, show.legend = TRUE, aes(colour = "blue"),
                size = 1.5) +
  stat_function(fun = fun.sacq.ltmf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.sacq.htmm, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  stat_function(fun = fun.sacq.ltmm, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red'='red','red4'='red4','blue'='blue','blue4'='blue4' ),
    labels = c('Overall Average','Female Student High TM','Female Student Low TM',
               'Male Student High TM', 'Male Student Low TM')) +
  ggtitle("Male and Female Adjustment Trajectories Depending on TM \nGiven Average Covariates")

#Intervention changing trajectory of at risk student SACQ Example
TMearly<- c(mean(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE)-
              sd(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
            mean(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
            mean(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE)+
              sd(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE))
fun.sacq.atrisk <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSSlow[x+1] +
```

```
    ef.sacq[4]* TMlow[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[1] + ef.sacq[7]*SES[1]}
fun.sacq.early <- function(x) {ef.sacq[1] + ef.sacq[2]*x +ef.sacq[3]*SPUSShigh[x+1] +
    ef.sacq[4]* TMearly[x+1] + ef.sacq[5]*GENDER[2] + ef.sacq[6]*GPA[1] + ef.sacq[7]*SES[1]}

## early intervention SACQ plot
plot.sacq.risk <- ggplot (lagdat, aes(x = time, y = SACQ.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.sacq.atrisk, n = 3, show.legend = TRUE, aes(colour = "red3"),
                size = 1.5) +
  stat_function(fun = fun.sacq.early, n = 3, show.legend = TRUE, aes(colour = "blue3"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean SACQ Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red3'='red3','blue3'='blue3' ),
    labels = c('Overall Average','At Risk with Early Intervention','At Risk Student')) +
  ggtitle("Female At Risk Students Adjustment Trajectories Depending on \nEarly and Late Intervention Given Average Covar
iates")

#### PSS Model Equations and Plot of Trajectories : ----
ef.pss <- fixef (mod4.pss)
#1-Intercept, 2-SPUSS, 3-TM, 4-Gender, 5-HGPA, 6-INCOME

#line for Male - Average GPA and average SES
fun.pss.m <- function(x) {ef.pss[1] + ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.f <- function(x) {ef.pss[1] + ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
#line for Low/high GPA Female - Average SES
fun.pss.lgpaf <- function(x) {ef.pss[1]  +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[1] + ef.pss[6]*SES[2]}
fun.pss.hgpaf <- function(x) {ef.pss[1]  +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[3] + ef.pss[6]*SES[2]}
fun.pss.lgpam <- function(x) {ef.pss[1]  +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[1] + ef.pss[6]*SES[2]}
fun.pss.hgpam <- function(x) {ef.pss[1]  +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[3] + ef.pss[6]*SES[2]}
#line for Low SES and High SES
fun.pss.fses1 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[1]}
fun.pss.fses2 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.fses3 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[3]}
fun.pss.fses4 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[4]}
fun.pss.mses1 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[1]}
fun.pss.mses2 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.mses3 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[3]}
fun.pss.mses4 <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[4]}
#high demo versus lowest demo
fun.pss.hdemo <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[3] + ef.pss[6]*SES[4]}
fun.pss.ldemo <- function(x) {ef.pss[1] +ef.pss[2]*SPUSS[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[1] + ef.pss[6]*SES[1]}
##SPUSS
fun.pss.hspussm <- function(x) {ef.pss[1] +ef.pss[2]*SPUSShigh[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.lspussm <- function(x) {ef.pss[1] +ef.pss[2]*SPUSSlow[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.hspussf <- function(x) {ef.pss[1] +ef.pss[2]*SPUSShigh[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.lspussf <- function(x) {ef.pss[1] +ef.pss[2]*SPUSSlow[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
##TM (had made a mistake so switcehd 2 with 3 to match coefficients)
fun.pss.htmm <- function(x) {ef.pss[1] +ef.pss[3]*TMhigh[x+1] +
    ef.pss[2]* SPUSS[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.ltmm <- function(x) {ef.pss[1] +ef.pss[3]*TMlow[x+1] +
    ef.pss[2]* SPUSS[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.htmf <- function(x) {ef.pss[1] +ef.pss[3]*TMhigh[x+1] +
    ef.pss[2]* SPUSS[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
```

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fun.pss.ltmf <- function(x) {ef.pss[1] +ef.pss[3]*TMlow[x+1] +
    ef.pss[3]* TM[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}

##hypothesis 5 b/c/d : lowTM high spuss, Low SPUSS high TM, Low and Low.
fun.pss.lowtmhighspuss <- function(x) {ef.pss[1] + +ef.pss[2]*SPUSShigh[x+1] +
    ef.pss[3]* TMlow[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.lowspusshightm <- function(x) {ef.pss[1] +ef.pss[2]*SPUSSlow[x+1] +
    ef.pss[3]* TMhigh[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}
fun.pss.low <- function(x) {ef.pss[1] + ef.pss[2]*SPUSSlow[x+1] +
    ef.pss[3]* TMlow[x+1] + ef.pss[4]*GENDER[1] + ef.pss[5]*GPA[2] + ef.pss[6]*SES[2]}

##SACQ Hypothesis 5 plots - comparing low/high SPUSS/TM
plot.pss.5 <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5),
                aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.lowtmhighspuss , n = 3, show.legend = TRUE, aes(colour = "blue1"),
                size = 1.5) +
  stat_function(fun = fun.pss.lowspusshightm , n = 3, show.legend = TRUE, aes(colour = "green1"),
                size = 1.5) +
  stat_function(fun = fun.pss.low , n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green1'='green1','blue1'='blue1',
              'red'='red'),
    labels = c('Overall Average','High SPUSS and Low TM','High TM and Low SPUSS',
               'Low on both SPUSS and TM')) +
  ggtitle("Perceived Stress Trajectories of Students with Varied \nSPUSS and TM Levels Given Average Covariates")

## Gender PSS plot
plot.pss.gender <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.m, n = 3, show.legend = TRUE, aes(colour = "red3"),
                size = 1.5) +
  stat_function(fun = fun.pss.f, n = 3, show.legend = TRUE, aes(colour = "blue3"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red3'='red3','blue3'='blue3' ),
    labels = c('Overall Average','Female Students','Male Students')) +
  ggtitle("Male and Female Perceived Stress Trajectories Given Average Covariates")

##HGPA PSS trajectory plot
plot.pss.hgpa <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.lgpaf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.pss.hgpaf, n = 3, show.legend = TRUE, aes(colour = "blue1"),
                size = 1.5) +
  stat_function(fun = fun.pss.lgpam, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  stat_function(fun = fun.pss.hgpam, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red4'='red4','red'='red','blue4'='blue4','blue1'='blue1' ),
    labels = c('Overall Average',"Female High HGPA","Female Low HGPA",'Male High HGPA', 'Male Low HGPA')) +
  ggtitle("Perceived Stress Trajectories of Students Depending on \nHigh School GPA Given Average Covariates")

##PSS SES trajectory Plot
plot.pss.ses <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5),
                aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.fses1 , n = 3, show.legend = TRUE, aes(colour = "green4"),
                size = 1.5) +
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  stat_function(fun = fun.pss.fses4 , n = 3, show.legend = TRUE, aes(colour = "green1"),
                size = 1.5) +
  stat_function(fun = fun.pss.mses1 , n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  stat_function(fun = fun.pss.mses4 , n = 3, show.legend = TRUE, aes(colour = "red1"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green1'='green1','green4'='green4',
              'red1'='red1','red4'='red4'),
    labels = c('Overall Average','Female Student Very High SES','Female Student Low SES',
               'Male Student Very High SES','Male Student Low SES')) +
  ggtitle("Perceived Stress Trajectories of Students Depending on Perceived \nSocio-Economic Status Given Average Covaria
tes")

## High Low Demo PSS Contrast
plot.pss.demo <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.hdemo, n = 3, show.legend = TRUE, aes(colour = "green3"),
                size = 1.5) +
  stat_function(fun = fun.pss.ldemo, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green3'='green3','red4'='red4' ),
    labels = c('Overall Average','High SES Male with High HGPA',
               'Low SES Female with Low HGPA')) +
  ggtitle("Contrasting Perceived Stress Trajectories of Students with High and Low \nAdvantages Given Average Covariates"
)

##SPUSS
plot.pss.spuss <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.hspussf, n = 3, show.legend = TRUE, aes(colour = "blue"),
                size = 1.5) +
  stat_function(fun = fun.pss.lspussf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.pss.hspussm, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  stat_function(fun = fun.pss.lspussm, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red'='red','red4'='red4','blue'='blue','blue4'='blue4' ),
    labels = c('Overall Average','Female Student High SPUSS','Female Student Low SPUSS',
               'Male Student High SPUSS', 'Male Student Low SPUSS')) +
  ggtitle("Male and Female Perceived Stress Trajectories Depending on SPUSS \nGiven Average Covariates")

##TM
plot.pss.tm <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.htmf, n = 3, show.legend = TRUE, aes(colour = "blue"),
                size = 1.5) +
  stat_function(fun = fun.pss.ltmf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.pss.htmm, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  stat_function(fun = fun.pss.ltmm, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red'='red','red4'='red4','blue'='blue','blue4'='blue4' ),
    labels = c('Overall Average','Female Student High TM','Female Student Low TM',
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              'Male Student High TM', 'Male Student Low TM')) +
  ggtitle("Male and Female Perceived Stress Trajectories Depending on TM \nGiven Average Covariates")

#Intervention changing trajectory of at risk student PSS Example
fun.pss.atrisk <- function(x) {ef.pss[1] + ef.pss[2]*SPUSSlow[x+1] +
    ef.pss[3]* TMlow[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[1] + ef.pss[6]*SES[1]}
fun.pss.early <- function(x) {ef.pss[1] + ef.pss[2]*SPUSShigh[x+1] +
    ef.pss[3]* TMearly[x+1] + ef.pss[4]*GENDER[2] + ef.pss[5]*GPA[1] + ef.pss[6]*SES[1]}

## early intervention PSS plot
plot.pss.risk <- ggplot (lagdat, aes(x = time, y = PSS.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
               show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.pss.atrisk, n = 3, show.legend = TRUE, aes(colour = "red3"),
               size = 1.5) +
  stat_function(fun = fun.pss.early, n = 3, show.legend = TRUE, aes(colour = "blue3"),
               size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean PSS Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red3'='red3','blue3'='blue3' ),
    labels = c('Overall Average','At Risk with Early Intervention','At Risk Student')) +
  ggtitle("Female At Risk Students Perceived Stress Trajectories Depending on \nEarly and Late Intervention Given Average
Covariates")

#### CESD Model Equations and Plot of Trajectories : ----

ef.cesdt <- fixef (mod4.cesdt)

#line for Male - Average GPA and average SES
fun.cesdt.m <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.f <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
#line for Low/high GPA Female - Average SES
fun.cesdt.lgpaf <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[1] + ef.cesdt[7]*SES[2]}
fun.cesdt.hgpaf <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[3] + ef.cesdt[7]*SES[2]}
fun.cesdt.lgpam <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[1] + ef.cesdt[7]*SES[2]}
fun.cesdt.hgpam <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[3] + ef.cesdt[7]*SES[2]}
#line for Low SES and High SES
fun.cesdt.fses1 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[1]}
fun.cesdt.fses2 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.fses3 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[3]}
fun.cesdt.fses4 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[4]}
fun.cesdt.mses1 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[1]}
fun.cesdt.mses2 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.mses3 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[3]}
fun.cesdt.mses4 <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[4]}
#high demo versus lowest demo
fun.cesdt.hdemo <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[3] + ef.cesdt[7]*SES[4]}
fun.cesdt.ldemo <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[1] + ef.cesdt[7]*SES[1]}
##SPUSS
fun.cesdt.hspussm <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSShigh[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.lspussm <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSSlow[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.hspussf <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSShigh[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.lspussf <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSSlow[x+1] +
    ef.cesdt[4]* TM[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
##TM
fun.cesdt.htmm <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
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    ef.cesdt[4]* TMhigh[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.ltmm <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TMlow[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.htmf <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TMhigh[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.ltmf <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSS[x+1] +
    ef.cesdt[4]* TMlow[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}

##hypothesis 5 b/c/d : lowTM high spuss, Low SPUSS high TM, Low and Low.
fun.cesdt.lowtmhighspuss <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSShigh[x+1] +
    ef.cesdt[4]* TMlow[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.lowspusshightm <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSSlow[x+1] +
    ef.cesdt[4]* TMhigh[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}
fun.cesdt.low <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSSlow[x+1] +
    ef.cesdt[4]* TMlow[x+1] + ef.cesdt[5]*GENDER[1] + ef.cesdt[6]*GPA[2] + ef.cesdt[7]*SES[2]}

##CESDT Hypothesis 5 plots - comparing low/high SPUSS/TM
plot.cesdt.5 <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5),
                aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.lowtmhighspuss , n = 3, show.legend = TRUE, aes(colour = "blue1"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.lowspusshightm , n = 3, show.legend = TRUE, aes(colour = "green1"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.low , n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green1'='green1','blue1'='blue1',
              'red'='red'),
    labels = c('Overall Average','High SPUSS and Low TM','High TM and Low SPUSS',
               'Low on both SPUSS and TM')) +
  ggtitle("Depression Rating Trajectories of Students with Varied SPUSS and TM Levels Given Average Covariates")

## Gender CESDT plot
plot.cesdt.gender <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.m, n = 3, show.legend = TRUE, aes(colour = "red3"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.f, n = 3, show.legend = TRUE, aes(colour = "blue3"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red3'='red3','blue3'='blue3' ),
    labels = c('Overall Average','Female Students','Male Students')) +
  ggtitle("Male and Female Depression Rating Trajectories Given Average Covariates")

##HGPA CESDT plot
plot.cesdt.hgpa <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.lgpaf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.hgpaf, n = 3, show.legend = TRUE, aes(colour = "blue1"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.lgpam, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.hgpam, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red4'='red4','red'='red','blue4'='blue4','blue1'='blue1' ),
    labels = c('Overall Average',"Female High HGPA","Female Low HGPA",'Male High HGPA', 'Male Low HGPA')) +
  ggtitle("Depression Rating Trajectories of Students Depending on \nHigh School GPA Given Average Covariates")

##CESDT SES Plot
plot.cesdt.ses <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
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```
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5),
                aes(colour = "black" , fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.fses1 , n = 3, show.legend = TRUE, aes(colour = "green4"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.fses4 , n = 3, show.legend = TRUE, aes(colour = "green1"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.mses1 , n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.mses4 , n = 3, show.legend = TRUE, aes(colour = "red1"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() + scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') +  guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green1'='green1','green4'='green4',
              'red1'='red1','red4'='red4'),
    labels = c('Overall Average','Female Student Very High SES','Female Student Low SES',
               'Male Student Very High SES','Male Student Low SES')) +
  ggtitle("Depression Rating Trajectories of Students Depending on Perceived \nSocio-Economic Status Given Average Covari
ates")

## High Low Demo CESDT Contrast
plot.cesdt.demo <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.hdemo, n = 3, show.legend = TRUE, aes(colour = "green3"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.ldemo, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','green3'='green3','red4'='red4' ),
    labels = c('Overall Average','High SES Male with High HGPA',
               'Low SES Female with Low HGPA')) +
  ggtitle("Contrasting Depression Rating Trajectories of Students with High and Low \nAdvantages Given Average Covariates
")

##SPUSS
plot.cesdt.spuss <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.hspussf, n = 3, show.legend = TRUE, aes(colour = "blue"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.lspussf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.hspussm, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.lspussm, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red'='red','red4'='red4','blue'='blue','blue4'='blue4' ),
    labels = c('Overall Average','Female Student High SPUSS','Female Student Low SPUSS',
               'Male Student High SPUSS', 'Male Student Low SPUSS')) +
  ggtitle("Male and Female Depression Rating Trajectories Depending on SPUSS \nGiven Average Covariates")


##TM
plot.cesdt.tm <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.htmf, n = 3, show.legend = TRUE, aes(colour = "blue"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.ltmf, n = 3, show.legend = TRUE, aes(colour = "blue4"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.htmm, n = 3, show.legend = TRUE, aes(colour = "red"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.ltmm, n = 3, show.legend = TRUE, aes(colour = "red4"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
```

```
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red'='red','red4'='red4','blue'='blue','blue4'='blue4' ),
    labels = c('Overall Average','Female Student High TM','Female Student Low TM',
               'Male Student High TM', 'Male Student Low TM')) +
  ggtitle("Male and Female Depression Rating Trajectories Depending on TM \nGiven Average Covariates")

#Intervention changing trajectory of at risk student CESDT Example
TMearly<- c(mean(lagdat$TM.mean[lagdat$time==0], na.rm = TRUE)-
              sd(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
            mean(lagdat$TM.mean[lagdat$time==1], na.rm = TRUE),
            mean(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE)+
              sd(lagdat$TM.mean[lagdat$time==2], na.rm = TRUE))
fun.cesdt.atrisk <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSSlow[x+1] +
    ef.cesdt[4]* TMlow[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[1] + ef.cesdt[7]*SES[1]}
fun.cesdt.early <- function(x) {ef.cesdt[1] + ef.cesdt[2]*x +ef.cesdt[3]*SPUSShigh[x+1] +
    ef.cesdt[4]* TMearly[x+1] + ef.cesdt[5]*GENDER[2] + ef.cesdt[6]*GPA[1] + ef.cesdt[7]*SES[1]}

## early intervention CESDT plot
plot.cesdt.risk <- ggplot (lagdat, aes(x = time, y = CESDT.mean)) +
  stat_summary( fun.data="mean_sdl", fun.args = list(mult=0.5), aes(colour = "black", fill= "grey84"),
                show.legend = TRUE,geom = 'smooth', se = TRUE) +
  stat_function(fun = fun.cesdt.atrisk, n = 3, show.legend = TRUE, aes(colour = "red3"),
                size = 1.5) +
  stat_function(fun = fun.cesdt.early, n = 3, show.legend = TRUE, aes(colour = "blue3"),
                size = 1.5) +
  xlab("Spring of the Academic Year") + ylab("Mean CESDT Scores") +
  theme_light() +  scale_x_continuous(breaks = c(0,1,2), labels = c("1","2","3")) +
  scale_fill_identity(guide = 'legend') + guides (fill = FALSE) +
  scale_colour_manual(
    name = 'Groups',
    values =c('black'='black','red3'='red3','blue3'='blue3' ),
    labels = c('Overall Average','At Risk with Early Intervention','At Risk Student')) +
  ggtitle("Female At Risk Students Depression Rating Trajectories Depending on \nEarly and Late Intervention Given Averag
e Covariates")

#### printing plots in order of discussion ----
plot.sacq.gender
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.sacq.ses
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.sacq.hgpa
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.sacq.demo
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.pss.gender
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.pss.ses
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.pss.hgpa
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.pss.demo
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.gender
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.ses
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.hgpa
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.demo
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.sacq.tm
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.sacq.spuss
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.sacq.5
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.sacq.risk
## Warning: Removed 1056 rows containing non-finite values (stat_summary).
plot.pss.tm
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.pss.spuss
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.pss.5
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.pss.risk
```

```
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.tm
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.spuss
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.5
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
plot.cesdt.risk
## Warning: Removed 1036 rows containing non-finite values (stat_summary).
```

```r
#### STUDY TWO – TIME MANAGEMENT INTERVENTION #####

library (xlsx)
library (tidyr)
library (car)

## Loading required package: carData

library (lattice)
library (reshape2)

##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
##     smiths

library (ggplot2)
library (stringr)
library (stargazer)

##
## Please cite as:

##  Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.

##  R package version 5.2.2. https://CRAN.R-project.org/package=stargazer

library (pander)
library (grid)
library (gridExtra)
library (plyr)
library (dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:plyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following object is masked from 'package:gridExtra':
##
##     combine

## The following object is masked from 'package:car':
##
##     recode

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library (magrittr)

##
## Attaching package: 'magrittr'

## The following object is masked from 'package:tidyr':
##
##     extract

library (effsize)
library (ggthemes)
library (scales)
library (apaTables)

## Warning: package 'apaTables' was built under R version 3.5.3
```

```r
#### Importing data and setup ----
dat<- read.xlsx("winter pre post.xlsx", 1)
#setting up labels
dat$intervention <- factor(dat$intervention,
                           levels = c(0,1),labels = c("Control","Intervention"))
dat$gender <- factor(dat$gender,
                     levels = c(1,2),labels = c("Male","Female"))



#long form for plots for select variables
dat.select <- dat[dat$post ==1, c("URPP","intervention","spuss_m","spuss_postm", "tm_m", "tm_postm",
                                  "sacq_m","sacq_postm", "pss_m","pss_postm", "cesd_m", "cesd_postm",
                                  "ego_pre", "ego_post","decision_pre", "decision_post", "mult_pre", "mult_post",
                                  "feedback_pre", "feedback_post", "commit_pre", "commit_post",
                                  "pomo_pre","pomo_post")]
#transform to undifferentiated long format with Reshape
dat.messy<-melt(data=dat.select,
                id.vars=c("URPP","intervention"),
                variable.name="var",value.name="value")
#seperating Time and Measure Columns
dat.sep <- separate(dat.messy,
                    var, into = c("measure", "time"), sep = "\\_")
#recoding Time to numeric based on semesters
dat.sep$time<-car::recode(dat.sep$time,"'m'=0;'post'=1;'pre'=0;'postm'=1", as.numeric=TRUE)
#Seperating the Variable Columns
dat.long = dcast(dat.sep, URPP + intervention + time  ~ measure, value.var = "value" )

#Setting up Labels
dat.long$time <- factor(dat.long$time,levels = c(0,1),labels = c("Pre","Post"))
dat.long$mult <- factor(dat.long$mult,levels = c(1,2,3,4,5),
                        labels = c("None","Know it slightly",
                                   "Know a few things", "Know a moderate amount","Know a fair bit"))
dat.long$commit <- factor(dat.long$commit,levels = c(1,2,3,4,5),
                        labels = c("None","Know it slightly",
                                   "Know a few things", "Know a moderate amount","Know a fair bit"))
dat.long$decision <- factor(dat.long$decision,levels = c(1,2,3,4,5),
                          labels = c("None","Know it slightly",
                                     "Know a few things", "Know a moderate amount","Know a fair bit"))
dat.long$ego <- factor(dat.long$ego,levels = c(1,2,3,4,5),
                            labels = c("None","Know it slightly",
                                       "Know a few things", "Know a moderate amount","Know a fair bit"))
dat.long$feedback <- factor(dat.long$feedback,levels = c(1,2,3,4,5),
                       labels = c("None","Know it slightly",
                                  "Know a few things", "Know a moderate amount","Know a fair bit"))
dat.long$pomo <- factor(dat.long$pomo,levels = c(1,2,3,4,5),
                            labels = c("None","Know it slightly",
                                       "Know a few things", "Know a moderate amount","Know a fair bit"))
#### SDI plots ----
par(bty="n") #no box around the plot options.
par(mfrow=c(2,4))

#sacq
Boxplot(dat$sacqisd, id.n = 2, labels = dat$URPP, col = "limegreen", main = "SACQ Pre Scores",ylim = c(0, 4),
        ylab = "Inter Item Standard Deviation")

## [1] 57 58

Boxplot(dat$sacqpostisd,id.n = 2, labels = dat$URPP, col = "limegreen", main = "SACQ Post Scores", ylim = c(0, 4),
        ylab = "")

#cesd
Boxplot(dat$cesdisd, id.n = 2, labels = dat$URPP, col = "limegreen", main = "CESD Pre Scores",ylim = c(0, 4),
        ylab = "Inter Item Standard Deviation")

Boxplot(dat$cesdpostisd,id.n = 2, labels = dat$URPP, col = "limegreen", main = "CESD Post Scores", ylim = c(0, 4),
        ylab = "")
#spuss
Boxplot(dat$spussisd, id.n = 2, labels = dat$URPP, col = "plum", main = "SPUSS Pre Scores",ylim = c(0, 4),
                   ylab = "Inter Item Standard Deviation")

Boxplot(dat$spusspostisd,id.n = 2, labels = dat$URPP, col = "plum", main = "SPUSS Post Scores", ylim = c(0, 4),
        ylab = "")
```

```r
#tm
Boxplot(dat$tmisd, id.n = 2, labels = dat$URPP, col = "plum", main = "TM pre",ylim = c(0, 4),
        ylab = "Inter Item Standard Deviation")

Boxplot(dat$tmpostisd,id.n = 2, labels = dat$URPP, col = "plum", main = "TM post", ylim = c(0, 4),
        ylab = "")
```

```
## [1] 5
```

```r
par(mfrow=c(1,1))


#### Chronbach Alphas Groups Combined at pre and post----
#df to store values
alphatable <- data.frame(c("SPUSS", "TM","SACQ","PSS","CESD"),c(1:5),c(1:5))
colnames(alphatable)<- c("Measure","Pre Alpha","Post Alpha")

#Spuss pre and post
#colnames(dat)[33:52] #checking column names
alphatable[1,2] <-psych::alpha(dat[33:52],check.keys=TRUE, warnings = FALSE)$total$std.alpha
#colnames(dat)[55:74] #checking column names
alphatable[1,3] <-psych::alpha(dat[55:74],check.keys=TRUE, warnings = FALSE)$total$std.alpha

#tm pre and post
#colnames(dat)[78:99] #checking column names
alphatable[2,2] <-psych::alpha(dat[78:99],check.keys=TRUE, warnings = FALSE)$total$std.alpha
#colnames(dat)[102:123] #checking column names
alphatable[2,3] <-psych::alpha(dat[102:123],check.keys=TRUE, warnings = FALSE)$total$std.alpha

# sacq pre and post
#colnames(dat)[127:150] #checking column names
alphatable[3,2] <-psych::alpha(dat[127:150],check.keys=TRUE, warnings = FALSE)$total$std.alpha
#colnames(dat)[153:176] #checking column names
alphatable[3,3] <-psych::alpha(dat[153:176],check.keys=TRUE, warnings = FALSE)$total$std.alpha

# pss pre and  post
#colnames(dat)[180:193] #checking column names
alphatable[4,2] <-psych::alpha(dat[180:193],check.keys=TRUE, warnings = FALSE)$total$std.alpha
#colnames(dat)[196:209] #checking column names
alphatable[4,3] <-psych::alpha(dat[196:209],check.keys=TRUE, warnings = FALSE)$total$std.alpha

# cesd pre and  post
#colnames(dat)[213:232] #checking column names
alphatable[5,2] <-psych::alpha(dat[213:232],check.keys=TRUE, warnings = FALSE)$total$std.alpha
#colnames(dat)[235:254] #checking column names
alphatable[5,3] <-psych::alpha(dat[235:254],check.keys=TRUE, warnings = FALSE)$total$std.alpha

pander (alphatable)
```

Measure	Pre Alpha	Post Alpha
SPUSS	0.8527	0.8744
TM	0.9082	0.9188
SACQ	0.8746	0.8848
PSS	0.8604	0.9179
CESD	0.872	0.8905

```r
#### demographics plots and analysis ----

##checking for differences between groups in demographics
#gender, ses, highschool gpa, and age
demgender <- xtabs(~dat$intervention +dat$gender )
chisq.test(demgender)
```

```
##
##  Pearson's Chi-squared test with Yates' continuity correction
##
## data:  demgender
## X-squared = 0.0024702, df = 1, p-value = 0.9604
```

```r
demincome <- xtabs(~dat$intervention +dat$ses )
chisq.test(demincome)

## Warning in chisq.test(demincome): Chi-squared approximation may be
## incorrect

##
##  Pearson's Chi-squared test
##
## data:  demincome
## X-squared = 1.3356, df = 3, p-value = 0.7207

hgpa.t <- t.test (dat$hgpa ~dat$intervention)
pander(hgpa.t)
```

Welch Two Sample t-test: `dat$hgpa` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
0.8643	56.93	0.3911	two.sided

mean in group Control	mean in group Intervention
80.76	78.97

```r
age.t <- t.test (dat$age ~dat$intervention)
pander(age.t)
```

Welch Two Sample t-test: `dat$age` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-1.516	56.54	0.135	two.sided

mean in group Control	mean in group Intervention
19.24	19.88

```r
#plots - gender accross two groups
gendertable =as.data.frame(prop.table(table( dat$gender,dat$intervention),2)*100)
genderplot <- ggplot(gendertable,aes(x=Var2,y=Freq,fill=Var1))+
  geom_bar(stat = "identity") +
  labs( title = "Gender Ratio in Control and Intervention Groups",
        y = "Percent", x = "", fill = "") +
  geom_text(aes( label = paste(round(Freq),"%"), y= Freq, group = Var1),
            position = position_stack(vjust = .5))
genderplot

#plots - ses accross two groups - mosaic plot
ses <- table (dat$ses,dat$intervention ) %>%
  set_colnames(c("Control","Intervention"))%>%
  set_rownames(c("Below Av.", "Av.", "Above Av.", "Sig. Above Av."))

mosaicplot(ses, type = "pearson", shade=TRUE, cex.axis = 1.1,
           main = "Self-Reported Income Distribution Accross Groups")

#HGPA plot
hsplot<-ggplot(data = dat, aes(x = intervention, y = hgpa, fill = intervention))+
  geom_boxplot() +theme(legend.position="none", axis.title.x = element_blank())+
  labs( title = "Self-Reported High School Averages of Students in Intervention and Control Groups") +
  scale_y_continuous(name = "High School Graduating Averege %",limits=c(0, 100))
hsplot

#AGE Plot
ageplot<-ggplot(data = dat, aes(x = intervention, y = age, fill = intervention))+
  geom_boxplot() +theme(legend.position="none", axis.title.x = element_blank())+
  labs( title = "Self-Reported Age") +
  scale_y_continuous(name = "Age in Years", limits=c(16,25))
ageplot

#### Descriptive Tables ----
# **Descriptive Tables at time one - one table for all **
#Variables to include: age, SES, HGPA, TM, SPUSS, SACQ, PSS, CESD

stargazer(dat[c("age","ses","hgpa","tm_m","spuss_m","sacq_m", "pss_m","cesd_m")], type = "text",
          title="Descriptive Statistics of Demographic and Scale Measures at the Initial Data Collection",
          digits=2, out="study2pre-descriptive.html", flip=FALSE, iqr = FALSE,median = TRUE,
```

```r
          covariate.labels=c("Age","Self-Reported Income","Self-Reported High School GPA",
                             "TMU (Mean)", "SPUSS (Mean)","SACQ (Mean)","PSS (Mean)", "CESD (Mean)"))
```

```
##
## Descriptive Statistics of Demographic and Scale Measures at the Initial Data Collection
## ==================================================================================
## Statistic                     N  Mean  St. Dev. Min  Pctl(25) Median Pctl(75) Max
## ----------------------------------------------------------------------------------
## Age                           59 19.61   1.72    18     18      19       21     25
## Self-Reported Income          59 2.03    0.85    1      1.5     2        2      4
## Self-Reported High School GPA 59 79.73   8.17    60     73.5    80       85     98
## TMU (Mean)                    59 2.53    0.59   1.36   2.11    2.55     2.91   3.91
## SPUSS (Mean)                  59 6.10    0.96   3.95   5.43    6.00     6.78   8.10
## SACQ (Mean)                   59 5.74    1.11   3.25   5.06    5.75     6.65   7.88
## PSS (Mean)                    59 1.71    0.55   0.71   1.36    1.64     2.00   3.00
## CESD (Mean)                   59 0.85    0.47   0.10   0.55    0.75     1.15   2.10
## ----------------------------------------------------------------------------------
```

```r
#**Descriptive Tables at time two - seperate for intervention and control  **
#control
stargazer(subset(dat[c("age","ses","hgpa","tm_postm","spuss_postm","sacq_postm",
                       "pss_postm","cesd_postm")], dat$intervention == "Control" & dat$post == 1),
          type = "text", digits=2, out="study2post-con.html", flip=FALSE, iqr = FALSE,median = TRUE,
          title="Descriptive Statistics of Demographic and Scale Measures post Workshop for Control Group",
          covariate.labels=c("Age","Self-Reported Income","Self-Reported High School GPA",
                             "TMU (Mean)", "SPUSS (Mean)","SACQ (Mean)","PSS (Mean)", "CESD (Mean)"))
```

```
##
## Descriptive Statistics of Demographic and Scale Measures post Workshop for Control Group
## ==================================================================================
## Statistic                     N  Mean  St. Dev. Min  Pctl(25) Median Pctl(75) Max
## ----------------------------------------------------------------------------------
## Age                           24 19.12   1.19    18     18      19       20     22
## Self-Reported Income          24 2.00    0.93    1      1       2        2      4
## Self-Reported High School GPA 24 80.42   6.78    70     76.2    80       83.5   96
## TMU (Mean)                    24 2.17    0.65   0.64   1.74    2.41     2.66   3.00
## SPUSS (Mean)                  24 6.31    1.02   4.25   5.80    6.40     6.81   7.90
## SACQ (Mean)                   24 5.03    1.06   2.96   4.31    5.06     5.93   6.75
## PSS (Mean)                    24 2.33    0.63   1.14   1.89    2.32     2.73   3.64
## CESD (Mean)                   24 1.23    0.53   0.25   0.74    1.23     1.66   2.05
## ----------------------------------------------------------------------------------
```

```r
#intervention
stargazer(subset(dat[c("age","ses","hgpa","tm_postm","spuss_postm","sacq_postm",
                       "pss_postm","cesd_postm")], dat$intervention == "Intervention" & dat$post == 1),
          type = "text", digits=2, out="study2post-int.html", flip=FALSE, iqr = FALSE,median = TRUE,
          title="Descriptive Statistics of Demographic and Scale Measures post Workshop for Intervention Group",
                    covariate.labels=c("Age","Self-Reported Income","Self-Reported High School GPA",
                             "TMU (Mean)", "SPUSS (Mean)","SACQ (Mean)","PSS (Mean)", "CESD (Mean)"))
```

```
##
## Descriptive Statistics of Demographic and Scale Measures post Workshop for Intervention Group
## ==================================================================================
## Statistic                     N  Mean  St. Dev. Min  Pctl(25) Median Pctl(75) Max
## ----------------------------------------------------------------------------------
## Age                           31 20.03   1.97    18    18.5     19       22     25
## Self-Reported Income          31 2.03    0.80    1      2       2        2      4
## Self-Reported High School GPA 31 78.81   9.38    60     70      75       87     98
## TMU (Mean)                    31 2.75    0.54   1.55   2.41    2.73     3.16   3.82
## SPUSS (Mean)                  31 6.39    1.05   4.20   5.60    6.30     7.12   8.60
## SACQ (Mean)                   31 6.08    1.01   4.42   5.52    5.75     6.79   8.29
## PSS (Mean)                    31 1.64    0.72   0.29   1.11    1.64     2.11   3.29
## CESD (Mean)                   31 1.12    0.50   0.45   0.80    1.05     1.38   2.55
## ----------------------------------------------------------------------------------
```

```r
#### Change in Process and Outcome measures from pre to post ----

#T-test of Difference scores for measuring change in SPUSS
spuss.t <- t.test (dat$spussdelta ~ dat$intervention)
pander(spuss.t)
```

Welch Two Sample t-test: `dat$spussdelta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
0.5221	45.51	0.6041	two.sided

mean in group Control	mean in group Intervention
0.2979	0.1581

```
cohen.d(spussdelta ~ intervention, data = dat)
```

```
##
## Cohen's d
##
## d estimate: -0.141907 (negligible)
## 95 percent confidence interval:
##        inf        sup
## -0.6879262  0.4041121
```

```
#plot change over time
spuss.p <- ggplot(dat.long,aes(x = time, y = spuss))+
  geom_dotplot( aes(color=intervention, fill=intervention),alpha = 0.4,
              dotsize = 0.4, binaxis='y', stackdir='center')+
  stat_smooth(aes (color=intervention, group = intervention) ,
             position=position_dodge(0.06), method="lm", se=FALSE)+
    stat_summary(aes (color=intervention, group = intervention),
               fun.data=mean_sdl, fun.args = list(mult=1),
               geom="errorbar", width=0.2, size = 1,  position=position_dodge(0.06) ) +
    stat_summary(aes (color=intervention, group = intervention),
               fun.y=mean, geom="point", shape= 15, size = 2.5, position=position_dodge(0.06))+
  labs(y = "SPUSS Mean", x = "Time", color = "Group Mean:", fill = "Individual Mean:",
       title = "Change in Student Perception of University Support & Structure Scores \n Post Workshop Between Interventi
on and Control Groups")
spuss.p
```

```
## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.
```

```
#T-test of Difference scores for measuring change in TM
tm.t <- t.test (dat$tmdelta ~ dat$intervention)
pander(tm.t)
```

Welch Two Sample t-test: `dat$tmdelta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-2.699	49.78	0.009464 * *	two.sided

mean in group Control	mean in group Intervention
-0.3087	0.1452

```
cohen.d(tmdelta ~ intervention, data = dat)
```

```
##
## Cohen's d
##
## d estimate: 0.7339487 (medium)
## 95 percent confidence interval:
##      inf      sup
## 0.170831 1.297066
```

```
#plot change over time
tm.p <- ggplot(dat.long,aes(x = time, y = tm))+
  geom_dotplot( aes(color=intervention, fill=intervention),alpha = 0.4,
              dotsize = 0.4, binaxis='y', stackdir='center')+
  stat_smooth(aes (color=intervention, group = intervention) ,
             position=position_dodge(0.06), method="lm", se=FALSE)+
  stat_summary(aes (color=intervention, group = intervention),
               fun.data=mean_sdl, fun.args = list(mult=1),
               geom="errorbar", width=0.2, size = 1,  position=position_dodge(0.06) ) +
  stat_summary(aes (color=intervention, group = intervention),
               fun.y=mean, geom="point", shape= 15, size = 2.5, position=position_dodge(0.06))+
  labs(y = "TM Mean", x = "Time", color = "Group Mean:", fill = "Individual Mean:",
       title = "Change in Time Management Scores \n Post Workshop Between Intervention and Control Groups")
tm.p
```

```
## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.
```

```r
#T-test of Difference scores for measuring change in SACQ-AA
sacq.t <- t.test (dat$sacqdelta ~ dat$intervention)
pander(sacq.t)
```

Welch Two Sample t-test: `dat$sacqdelta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-3.764	51.24	0.0004317 * * *	two.sided

mean in group Control	mean in group Intervention
-0.6406	0.2728

```r
cohen.d(sacqdelta ~ intervention, data = dat)
```

```
##
## Cohen's d
##
## d estimate: 1.023596 (large)
## 95 percent confidence interval:
##      inf      sup
## 0.444183 1.603009
```

```r
#plot change over time
sacq.p <- ggplot(dat.long,aes(x = time, y = sacq))+
  geom_dotplot( aes(color=intervention, fill=intervention),alpha = 0.4,
              dotsize = 0.4, binaxis='y', stackdir='center')+
  stat_smooth(aes (color=intervention, group = intervention) ,
            position=position_dodge(0.06), method="lm", se=FALSE)+
  stat_summary(aes (color=intervention, group = intervention),
             fun.data=mean_sdl, fun.args = list(mult=1),
             geom="errorbar", width=0.2, size = 1,  position=position_dodge(0.06) ) +
  stat_summary(aes (color=intervention, group = intervention),
             fun.y=mean, geom="point", shape= 15, size = 2.5, position=position_dodge(0.06))+
  labs(y = "SACQ-AA Mean", x = "Time", color = "Group Mean:", fill = "Individual Mean:",
       title = "Change in Academic Adjustment Scores \n Post Workshop Between Intervention and Control Groups")
sacq.p
```

```
## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.
```

```r
#T-test of Difference scores for measuring change in PSS
pss.t <- t.test (dat$pssdelta ~ dat$intervention)
pander(pss.t)
```

Welch Two Sample t-test: `dat$pssdelta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
2.907	52.78	0.00532 * *	two.sided

mean in group Control	mean in group Intervention
0.5565	0.006912

```r
cohen.d(pssdelta ~ intervention, data = dat)
```

```
##
## Cohen's d
##
## d estimate: -0.7911009 (medium)
## 95 percent confidence interval:
##        inf        sup
## -1.3570419 -0.2251599
```

```r
#plot change over time
pss.p <- ggplot(dat.long,aes(x = time, y = pss))+
  geom_dotplot( aes(color=intervention, fill=intervention),alpha = 0.4,
              dotsize = 0.4, binaxis='y', stackdir='center')+
  stat_smooth(aes (color=intervention, group = intervention) ,
            position=position_dodge(0.06), method="lm", se=FALSE)+
  stat_summary(aes (color=intervention, group = intervention),
             fun.data=mean_sdl, fun.args = list(mult=1),
             geom="errorbar", width=0.2, size = 1,  position=position_dodge(0.06) ) +
  stat_summary(aes (color=intervention, group = intervention),
```

```
               fun.y=mean, geom="point", shape= 15, size = 2.5, position=position_dodge(0.06))+
  labs(y = "PSS Mean", x = "Time", color = "Group Mean:", fill = "Individual Mean:",
       title = "Change in Perceived Stress Scores \n Post Workshop Between Intervention and Control Groups")
pss.p

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

#T-test of Difference scores for measuring change in CESD
cesd.t <- t.test (dat$cesddelta ~ dat$intervention)
pander(cesd.t)
```

Welch Two Sample t-test: `dat$cesddelta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
1.335	44.03	0.1888	two.sided

mean in group Control	mean in group Intervention
0.4354	0.2726

```
cohen.d(cesddelta ~ intervention, data = dat)

##
## Cohen's d
##
## d estimate: -0.3627464 (small)
## 95 percent confidence interval:
##        inf        sup
## -0.9124853  0.1869925

#plot change over time
cesd.p <- ggplot(dat.long,aes(x = time, y = cesd))+
  geom_dotplot( aes(color=intervention, fill=intervention),alpha = 0.4,
                dotsize = 0.4, binaxis='y', stackdir='center')+
  stat_smooth(aes (color=intervention, group = intervention) ,
              position=position_dodge(0.06), method="lm", se=FALSE)+
  stat_summary(aes (color=intervention, group = intervention),
               fun.data=mean_sdl, fun.args = list(mult=1),
               geom="errorbar", width=0.2, size = 1,  position=position_dodge(0.06) ) +
  stat_summary(aes (color=intervention, group = intervention),
               fun.y=mean, geom="point", shape= 15, size = 2.5, position=position_dodge(0.06))+
  labs(y = "CESD Mean", x = "Time", color = "Group Mean:", fill = "Individual Mean:",
       title = "Change in Depression Scores \n Post Workshop Between Intervention and Control Groups")
cesd.p

## `stat_bindot()` using `bins = 30`. Pick better value with `binwidth`.

#### Is the change in outcome scores related to process variables (controlling for intervention) ----

#looking at sacq changes
sacq.reg <- lm ( sacqdelta ~ spussdelta + tmdelta + intervention, data = dat)
summary(sacq.reg)

##
## Call:
## lm(formula = sacqdelta ~ spussdelta + tmdelta + intervention,
##     data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.14857 -0.54270 -0.05547  0.57607  1.68870
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -0.484260   0.191929  -2.523  0.01479 *
## spussdelta              -0.007197   0.124632  -0.058  0.95418
## tmdelta                  0.499562   0.194588   2.567  0.01323 *
## interventionIntervention  0.685730   0.252533   2.715  0.00901 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8636 on 51 degrees of freedom
##   (4 observations deleted due to missingness)
```

```
## Multiple R-squared:  0.3002, Adjusted R-squared:  0.2591
## F-statistic: 7.293 on 3 and 51 DF,  p-value: 0.0003675

sacq.regresid <- data.frame(resid(sacq.reg))
colnames(sacq.regresid) <- c("resid")

ggplot(sacq.regresid, aes(x = resid)) +  theme_bw() +
  geom_histogram(aes(y =..density..),
                 breaks = seq(-3, 3, by = 0.25),
                 colour = "white", fill = "cornflowerblue", size = 0.1) +
  stat_function(fun = dnorm, args = list(mean = mean(sacq.regresid$resid), sd = sd(sacq.regresid$resid)),
                size =2, col = "darkred" ) +
  labs(y = "Residual Density", x = "Residuals",
       title = "Distribution of Residuals from Regression of Process Variables on SACQ")

plot(sacq.reg, which = 5)

#looking at pss changes
pss.reg <- lm ( pssdelta ~ spussdelta + tmdelta +intervention  , data = dat)
summary(pss.reg)

##
## Call:
## lm(formula = pssdelta ~ spussdelta + tmdelta + intervention,
##     data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.75213 -0.50421  0.06684  0.50520  1.37066
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)               0.45986    0.15229   3.020  0.00395 **
## spussdelta               -0.08365    0.09889  -0.846  0.40158
## tmdelta                  -0.39393    0.15440  -2.551  0.01377 *
## interventionIntervention -0.38254    0.20038  -1.909  0.06189 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6853 on 51 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.2491, Adjusted R-squared:  0.205
## F-statistic: 5.641 on 3 and 51 DF,  p-value: 0.002041

pss.regresid <- data.frame(resid(pss.reg))
colnames(pss.regresid) <- c("resid")

ggplot(pss.regresid, aes(x = resid)) +  theme_bw() +
  geom_histogram(aes(y =..density..),
                 breaks = seq(-3, 3, by = 0.25),
                 colour = "white", fill = "cornflowerblue", size = 0.1) +
  stat_function(fun = dnorm, args = list(mean = mean(pss.regresid$resid), sd = sd(pss.regresid$resid)),
                size =2, col = "darkred" ) +
  labs(y = "Residual Density", x = "Residuals",
       title = "Distribution of Residuals from Regression of Process Variables on PSS")

plot(pss.reg,  which = 5)

#creating regression tables APA style using Stargazer
stargazer (sacq.reg, pss.reg,  type = "text", out="regressiontable_changescores.html",
           single.row = TRUE, model.numbers = FALSE,
           dep.var.labels=c("Change in Adjustment Ratings","Change in Perceived Stress Ratings"),
           covariate.labels=c("Change in Perception of  Suppurt and Structure Scores",
                              "Change in Time Management Scores",
                              "Attended Intervention") )

##
## ==================================================================================================
##                                                                      Dependent variable:
##                                                         ------------------------------------------
##                                                         Change in Adjustment Ratings Change in Perceived Stress Ratings
## --------------------------------------------------------------------------------------------------
## Change in Perception of Suppurt and Structure Scores        -0.007 (0.125)                -0.084 (0.099)
## Change in Time Management Scores                           0.500** (0.195)               -0.394** (0.154)
```

```
## Attended Intervention                          0.686*** (0.253)          -0.383* (0.200)
## Constant                                       -0.484** (0.192)          0.460*** (0.152)
## ---------------------------------------------------------------------------------------------------------
## Observations                                         55                        55
## R2                                                 0.300                     0.249
## Adjusted R2                                        0.259                     0.205
## Residual Std. Error (df = 51)                      0.864                     0.685
## F Statistic (df = 3; 51)                          7.293***                  5.641***
## =========================================================================================================
## Note:                                                          *p<0.1; **p<0.05; ***p<0.01
```

```r
#creating regression tables APA style using APA tables
apa.reg.table(sacq.reg, filename = "regressiontable_sacqchange.doc")
```

```
##
## MBESS package needs to be installed to calculate R2 confidence intervals.

##
##
## Regression results using sacqdelta as the criterion
##
##
##                Predictor      b       b_95%_CI sr2  sr2_95%_CI
##              (Intercept) -0.48* [-0.87, -0.10]
##               spussdelta  -0.01  [-0.26, 0.24] .00 [-.00, .00]
##                  tmdelta  0.50*   [0.11, 0.89] .09 [-.04, .22]
##  interventionIntervention 0.69**   [0.18, 1.19] .10 [-.03, .24]
##
##
##
##           Fit
##
##
##
##
##    R2 = .300**
##  95% CI[NA,NA]
##
##
## Note. A significant b-weight indicates the semi-partial correlation is also significant.
## b represents unstandardized regression weights.
## sr2 represents the semi-partial correlation squared.
## Square brackets are used to enclose the lower and upper limits of a confidence interval.
## * indicates p < .05. ** indicates p < .01.
##
```

```r
apa.reg.table(pss.reg, filename = "regressiontable_psschange.doc")
```

```
##
## MBESS package needs to be installed to calculate R2 confidence intervals.

##
##
## Regression results using pssdelta as the criterion
##
##
##                Predictor      b       b_95%_CI sr2  sr2_95%_CI
##              (Intercept) 0.46**   [0.15, 0.77]
##               spussdelta  -0.08  [-0.28, 0.11] .01 [-.04, .06]
##                  tmdelta -0.39* [-0.70, -0.08] .10 [-.04, .23]
##  interventionIntervention  -0.38  [-0.78, 0.02] .05 [-.05, .16]
##
##
##
##           Fit
##
##
##
##
##    R2 = .249**
##  95% CI[NA,NA]
##
##
## Note. A significant b-weight indicates the semi-partial correlation is also significant.
## b represents unstandardized regression weights.
```

```
## sr2 represents the semi-partial correlation squared.
## Square brackets are used to enclose the lower and upper limits of a confidence interval.
## * indicates p < .05. ** indicates p < .01.
##

#### Change in Knowledge ----

##Change in *multi tasking*
#testing change with wilcoxon signed rank test in both groups pre/post
pander (t.test(dat$mult_pre [dat$intervention == "Intervention" ],
            dat$mult_post [dat$intervention == "Intervention"], paired=TRUE))
```

Paired t-test: `dat$mult_pre[dat$intervention == "Intervention"]` and `dat$mult_post[dat$intervention == "Intervention"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-9.627	30	1.1e-10 * * *	two.sided

mean of the differences
-2.129

```
pander (t.test(dat$mult_pre [dat$intervention == "Control" ],
                    dat$mult_post [dat$intervention == "Control"], paired=TRUE))
```

Paired t-test: `dat$mult_pre[dat$intervention == "Control"]` and `dat$mult_post[dat$intervention == "Control"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-4.047	23	0.000501 * * *	two.sided

mean of the differences
-0.9583

```
#T-test of Difference scores for change in knowledge
dat$mult_delta <- 0
dat$mult_delta [dat$intervention == "Intervention"] <-
  dat$mult_post [dat$intervention == "Intervention"]- dat$mult_pre [dat$intervention == "Intervention" ]
dat$mult_delta [dat$intervention == "Control"] <-
  dat$mult_post [dat$intervention == "Control"]- dat$mult_pre [dat$intervention == "Control" ]
mult.t <- t.test (dat$mult_delta ~ dat$intervention)
pander(mult.t)
```

Welch Two Sample t-test: `dat$mult_delta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-3.613	50.92	0.0006924 * * *	two.sided

mean in group Control	mean in group Intervention
0.9583	2.129

```
#plot of change
mult.gg <- ggplot( dat.long, aes( x= time, fill = mult)) +
  geom_bar()+  scale_fill_brewer(palette = "YlGn")+
  geom_text(aes( label = ..count..),
            position = position_stack(vjust = 0.5),stat= "count") +
  facet_wrap(intervention ~ ., scales = "free_y", strip.position = "left") + theme_minimal()+
  theme( axis.text.y=element_blank(),legend.position="bottom", plot.title = element_text(hjust = 0.5)) +
  labs(title ="Change in First Year Students' Self-reported Knowledge of the Effects of Multitasking on Learning post Wor
kshop") +
  labs(fill = "Self-Reported Knowledge", y = "", x = "Number of Students who Endorsed each Knowledge Level Category")
mult.gg

##Change in *precommitment*
#testing change with wilcoxon signed rank test in both groups pre/post
pander (t.test(dat$commit_pre [dat$intervention == "Intervention" ],
                    dat$commit_post [dat$intervention == "Intervention"], paired=TRUE))
```

Paired t-test: `dat$commit_pre[dat$intervention == "Intervention"]` and `dat$commit_post[dat$intervention == "Intervention"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-9.87	30	6.206e-11 * * *	two.sided

mean of the differences
-1.968

```r
pander (t.test(dat$commit_pre [dat$intervention == "Control" ],
                   dat$commit_post [dat$intervention == "Control"], paired=TRUE))
```

Paired t-test: `dat$commit_pre[dat$intervention == "Control"]` and `dat$commit_post[dat$intervention == "Control"]`

Test statistic	df	P value	Alternative hypothesis	mean of the differences
-1	23	0.3277	two.sided	-0.125

```r
#T-test of Difference scores for change in knowledge
dat$commit_delta <- 0
dat$commit_delta [dat$intervention == "Intervention"] <-
  dat$commit_post [dat$intervention == "Intervention"]- dat$commit_pre [dat$intervention == "Intervention" ]
dat$commit_delta [dat$intervention == "Control"] <-
  dat$commit_post [dat$intervention == "Control"]- dat$commit_pre [dat$intervention == "Control" ]
commit.t <- t.test (dat$commit_delta ~ dat$intervention)
pander(commit.t)
```

Welch Two Sample t-test: `dat$commit_delta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-7.831	48.45	3.733e-10 * * *	two.sided

mean in group Control	mean in group Intervention
0.125	1.968

```r
#plot of change
commit.gg <- ggplot( dat.long, aes( x = time, fill = commit)) +
  geom_bar()+  scale_fill_brewer(palette = "YlGn")+
  geom_text(aes( label = ..count..),
            position = position_stack(vjust = 0.5),stat= "count") +
  facet_wrap(intervention ~ ., scales = "free_y", strip.position = "left") + theme_minimal()+
  theme( axis.text.y=element_blank(),legend.position="bottom", plot.title = element_text(hjust = 0.5)) +
  labs(title ="Change in First Year Students' Self-reported Knowledge of Precommitment Strategies post Workshop") +
  labs(fill = "Self-Reported Knowledge", y = "", x = "Number of Students who Endorsed each Knowledge Level Category")
commit.gg

##Change in *decision fatigue*
#testing change with wilcoxon signed rank test in both groups pre/post
pander (t.test(dat$decision_pre [dat$intervention == "Intervention" ],
                   dat$decision_post [dat$intervention == "Intervention"], paired=TRUE))
```

Paired t-test: `dat$decision_pre[dat$intervention == "Intervention"]` and `dat$decision_post[dat$intervention == "Intervention"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-15.24	30	1.159e-15 * * *	two.sided

mean of the differences
-2.613

```r
pander (t.test(dat$decision_pre [dat$intervention == "Control" ],
                   dat$decision_post [dat$intervention == "Control"], paired=TRUE))
```

Paired t-test: `dat$decision_pre[dat$intervention == "Control"]` and `dat$decision_post[dat$intervention == "Control"]`

Test statistic	df	P value	Alternative hypothesis	mean of the differences
-1.415	23	0.1703	two.sided	-0.2083

```r
#T-test of Difference scores for change in knowledge
dat$decision_delta <- 0
dat$decision_delta [dat$intervention == "Intervention"] <-
  dat$decision_post [dat$intervention == "Intervention"]- dat$decision_pre [dat$intervention == "Intervention" ]
dat$decision_delta [dat$intervention == "Control"] <-
  dat$decision_post [dat$intervention == "Control"]- dat$decision_pre [dat$intervention == "Control" ]
decision.t <- t.test (dat$decision_delta ~ dat$intervention)
pander(decision.t)
```

Welch Two Sample t-test: `dat$decision_delta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-10.64	52.98	9.253e-15 * * *	two.sided

mean in group Control	mean in group Intervention
0.2083	2.613

```
#plot of change
decision.gg <- ggplot( dat.long, aes( x = time, fill = decision)) +
  geom_bar()+  scale_fill_brewer(palette = "YlGn")+
  geom_text(aes( label = ..count..),
            position = position_stack(vjust = 0.5),stat= "count") +
  facet_wrap(intervention ~ ., scales = "free_y", strip.position = "left") + theme_minimal()+
  theme( axis.text.y=element_blank(),legend.position="bottom", plot.title = element_text(hjust = 0.5)) +
  labs(title ="Change in First Year Students' Self-reported Knowledge of Decision Fatigue post Workshop") +
  labs(fill = "Self-Reported Knowledge", y = "", x = "Number of Students who Endorsed each Knowledge Level Category")
decision.gg

##Change in *ego depletion*
#testing change with wilcoxon signed rank test in both groups pre/post
pander (t.test(dat$ego_pre [dat$intervention == "Intervention" ],
                    dat$ego_post [dat$intervention == "Intervention"], paired=TRUE))
```

Paired t-test: `dat$ego_pre[dat$intervention == "Intervention"]` and `dat$ego_post[dat$intervention == "Intervention"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-11.57	30	1.377e-12 * * *	two.sided

mean of the differences
-2.129

```
pander (t.test(dat$ego_pre [dat$intervention == "Control" ],
                    dat$ego_post [dat$intervention == "Control"], paired=TRUE))
```

Paired t-test: `dat$ego_pre[dat$intervention == "Control"]` and `dat$ego_post[dat$intervention == "Control"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-7.014	23	3.788e-07 * * *	two.sided

mean of the differences
-1.625

```
#T-test of Difference scores for change in knowledge
dat$ego_delta <- 0
dat$ego_delta [dat$intervention == "Intervention"] <-
  dat$ego_post [dat$intervention == "Intervention"]- dat$ego_pre [dat$intervention == "Intervention" ]
dat$ego_delta [dat$intervention == "Control"] <-
  dat$ego_post [dat$intervention == "Control"]- dat$ego_pre [dat$intervention == "Control" ]
ego.t <- t.test (dat$ego_delta ~ dat$intervention)
pander(ego.t)
```

Welch Two Sample t-test: `dat$ego_delta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-1.704	46.87	0.09506	two.sided

mean in group Control	mean in group Intervention
1.625	2.129

```
#plot of change
ego.gg <- ggplot( dat.long, aes( x = time, fill = ego)) +
  geom_bar()+  scale_fill_brewer(palette = "YlGn")+
  geom_text(aes( label = ..count..),
            position = position_stack(vjust = 0.5),stat= "count") +
  facet_wrap(intervention ~ ., scales = "free_y", strip.position = "left") + theme_minimal()+
  theme( axis.text.y=element_blank(),legend.position="bottom", plot.title = element_text(hjust = 0.5)) +
  labs(title ="Change in First Year Students' Self-reported Knowledge of Ego Depletion post Workshop") +
  labs(fill = "Self-Reported Knowledge", y = "", x = "Number of Students who Endorsed each Knowledge Level Category")
ego.gg
```

```r
##Change in *pomodoro*
#testing change with wilcoxon signed rank test in both groups pre/post
pander (t.test(dat$pomo_pre [dat$intervention == "Intervention" ],
                   dat$pomo_post [dat$intervention == "Intervention"], paired=TRUE))
```

Paired t-test: `dat$pomo_pre[dat$intervention == "Intervention"]` and `dat$pomo_post[dat$intervention == "Intervention"]` (continued below)

Test statistic	df	P value	Alternative hypothesis
-12.54	30	1.84e-13 * * *	two.sided

mean of the differences
-3.097

```r
pander (t.test(dat$pomo_pre [dat$intervention == "Control" ],
                   dat$pomo_post [dat$intervention == "Control"], paired=TRUE))
```

Paired t-test: `dat$pomo_pre[dat$intervention == "Control"]` and `dat$pomo_post[dat$intervention == "Control"]`

Test statistic	df	P value	Alternative hypothesis	mean of the differences
-0.1705	23	0.8661	two.sided	-0.04167

```r
#T-test of Difference scores for change in knowledge
dat$pomo_delta <- 0
dat$pomo_delta [dat$intervention == "Intervention"] <-
  dat$pomo_post [dat$intervention == "Intervention"]- dat$pomo_pre [dat$intervention == "Intervention" ]
dat$pomo_delta [dat$intervention == "Control"] <-
  dat$pomo_post [dat$intervention == "Control"]- dat$pomo_pre [dat$intervention == "Control" ]
pomo.t <- t.test (dat$pomo_delta ~ dat$intervention)
pander(pomo.t)
```

Welch Two Sample t-test: `dat$pomo_delta` by `dat$intervention` (continued below)

Test statistic	df	P value	Alternative hypothesis
-8.794	52.21	6.987e-12 * * *	two.sided

mean in group Control	mean in group Intervention
0.04167	3.097

```r
#plot of change
pomo.gg <- ggplot( dat.long, aes( x = time, fill = pomo)) +
  geom_bar()+  scale_fill_brewer(palette = "YlGn")+
  geom_text(aes( label = ..count..),
            position = position_stack(vjust = 0.5),stat= "count") +
  facet_wrap(intervention ~ ., scales = "free_y", strip.position = "left") + theme_minimal()+
  theme( axis.text.y=element_blank(),legend.position="bottom", plot.title = element_text(hjust = 0.5)) +
  labs(title ="Change in First Year Students' Self-reported Knowledge of Pomodoro Technique post Workshop") +
  labs(fill = "Self-Reported Knowledge", y = "", x = "Number of Students who Endorsed each Knowledge Level Category")
pomo.gg

#### Satisfaction Plot ----
sat.t <- data.frame(apply(dat[c("q1", "q2","q3","q4","q5")], 2, table))
sat.t <- cbind( c(1,2,3,4,5),sat.t)

#transform to undifferentiated long format with Reshape
sat.melt <-melt(data=sat.t, id.vars =c(sat.t[1]),variable.name="var",value.name="value")
colnames (sat.melt) <- c("Rating","Question","Responses")
sat.melt$Rating <- factor(sat.melt$Rating,levels = c(1,2,3,4,5),
                          labels = c("Strongly Disagree","Disagree",
                                     "Neither Agree or Disagree","Agree", "Strongly Agree"))

# Calculate percentages and label positions
sat.summary = sat.melt %>% group_by(Question, Rating) %>%
  dplyr::summarise(Responses = sum(Responses)) %>%   # Within each Brand, sum all values in each Category
  dplyr::mutate(Percent = round(Responses/sum(Responses)*100,digits = 1) )
sat.summary$rounded <- round (sat.summary$Percent, digits = 0)


#plot the satisfaction percentages
ggplot(sat.summary, aes(x=Question, y=Percent, fill=Rating)) +
    geom_bar(stat='identity') + coord_flip() +
  geom_text(aes(label= paste0(rounded,"%")),
```

```r
            position=position_stack(vjust=0.5), colour="grey88")  +
  theme(legend.position="bottom",axis.title.x = element_blank(), axis.title.y = element_blank(),
        axis.text.y = element_text(size=14), axis.ticks.y = element_blank(),
        axis.text.x = element_blank(), plot.title = element_text(size=16)) +
  scale_fill_brewer(palette = "RdYlGn")+
  labs(title ="Students' Satisfaction Ratings of the Intervention Workshop")+
  scale_x_discrete(labels = c("I found the workshop useful",
                              "I would recommend the workshop to a friend",
                              "The length of the workshop was appropriate",
                              "I have used tools and techniques that I\nlearned in the workshop during this semester",
                              "I believe attending the workshop\nhelped me do better academically"),
                   position = "top")

#### GPA prediction by intervention  using block regression----
m1 <- lm (finalgrade ~ ses + hgpa  , data = dat [dat$post==1])
m2 <- lm (finalgrade ~ ses + hgpa + intervention, data = dat[dat$post==1])
m3 <- lm (finalgrade ~ ses + hgpa*intervention, data = dat[dat$post==1])

summary(m1)

##
## Call:
## lm(formula = finalgrade ~ ses + hgpa, data = dat[dat$post ==
##     1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.4882  -8.1837   0.5693   8.4121  18.0353
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  34.5027    13.9116   2.480   0.0164 *
## ses           2.6855     1.7499   1.535   0.1309
## hgpa          0.4190     0.1789   2.342   0.0230 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.63 on 52 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.162,  Adjusted R-squared:  0.1297
## F-statistic: 5.025 on 2 and 52 DF,  p-value: 0.01011

summary(m2)

##
## Call:
## lm(formula = finalgrade ~ ses + hgpa + intervention, data = dat[dat$post ==
##     1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.2255  -5.6503   0.8376   7.8863  21.9083
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)               26.7946    13.4076   1.998  0.05101 .
## ses                        2.4911     1.6507   1.509  0.13744
## hgpa                       0.4675     0.1695   2.758  0.00805 **
## interventionIntervention   7.5233     2.7385   2.747  0.00829 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.02 on 51 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:   0.27,  Adjusted R-squared:  0.2271
## F-statistic: 6.288 on 3 and 51 DF,  p-value: 0.001031

summary(m3)

##
## Call:
## lm(formula = finalgrade ~ ses + hgpa * intervention, data = dat[dat$post ==
##     1])
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.4416  -5.8091   0.5047   6.8313  20.3791
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  -11.0383    24.3612  -0.453  0.65243
## ses                            2.1962     1.6212   1.355  0.18161
## hgpa                           0.9453     0.3078   3.072  0.00344 **
## interventionIntervention      60.2750    28.7600   2.096  0.04118 *
## hgpa:interventionIntervention  -0.6595     0.3580  -1.842  0.07138 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.788 on 50 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.3164, Adjusted R-squared:  0.2617
## F-statistic: 5.785 on 4 and 50 DF,  p-value: 0.0006607
```

```
anova(m1, m2)
```

```
## Analysis of Variance Table
##
## Model 1: finalgrade ~ ses + hgpa
## Model 2: finalgrade ~ ses + hgpa + intervention
##   Res.Df    RSS Df Sum of Sq      F   Pr(>F)
## 1     52 5872.9
## 2     51 5115.8  1    757.05 7.5471 0.008287 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(m2, m3)
```

```
## Analysis of Variance Table
##
## Model 1: finalgrade ~ ses + hgpa + intervention
## Model 2: finalgrade ~ ses + hgpa * intervention
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1     51 5115.8
## 2     50 4790.7  1    325.16 3.3937 0.07138 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
delta.r=summary(m2)$adj.r.squared - summary(m1)$adj.r.squared
delta.rr=summary(m3)$adj.r.squared - summary(m2)$adj.r.squared
paste ("Change in Adjusted R Square m1 to m2 = ", delta.r)
```

```
## [1] "Change in Adjusted R Square m1 to m2 =  0.0973179957241905"
```

```
paste ("Change in Adjusted R Square m2 to m3 = ", delta.rr)
```

```
## [1] "Change in Adjusted R Square m2 to m3 =  0.0346520771816227"
```

```
#checking assumptions by plotting residuals and influencial points
gpa.regresid <- data.frame(resid(m2))
colnames(gpa.regresid) <- c("resid")

ggplot(gpa.regresid, aes(x = resid)) +  theme_bw() +
  geom_histogram(aes(y =..density..),
                 breaks = seq(-30, 30, by = 5),
                 colour = "white", fill = "cornflowerblue", size = 0.1) +
  stat_function(fun = dnorm, args = list(mean = mean(gpa.regresid$resid), sd = sd(gpa.regresid$resid)),
                size =2, col = "darkred" ) +
  labs(y = "Residual Density", x = "Residuals",
       title = "Distribution of Residuals from Regression of Intervention, SES, and HGPA on GPA")

plot(m2)

#output with APA tables
stargazer (m1,m2,m3,   type = "text", out="regressiontable_gpa.html",
           single.row = TRUE, model.numbers = TRUE,
           dep.var.labels=c("Final Course Grade"),
           covariate.labels=c("Self-Reported SES",
```

```r
                              "Highschool GPA",
                              "Intervention Workshop", "Intervention X Highshool GPA") )
```

```
##
## =============================================================================================
##                                                      Dependent variable:
##                              ---------------------------------------------------------------
##                                                       Final Course Grade
##                                        (1)                   (2)                   (3)
## ---------------------------------------------------------------------------------------------
## Self-Reported SES                2.686 (1.750)         2.491 (1.651)         2.196 (1.621)
## Highschool GPA                  0.419** (0.179)       0.468*** (0.170)      0.945*** (0.308)
## Intervention Workshop                                 7.523*** (2.739)      60.275** (28.760)
## Intervention X Highshool GPA                                                 -0.660* (0.358)
## Constant                       34.503** (13.912)     26.795* (13.408)      -11.038 (24.361)
## ---------------------------------------------------------------------------------------------
## Observations                           55                    55                    55
## R2                                   0.162                 0.270                 0.316
## Adjusted R2                          0.130                 0.227                 0.262
## Residual Std. Error             10.627 (df = 52)      10.015 (df = 51)       9.788 (df = 50)
## F Statistic                   5.025** (df = 2; 52) 6.288*** (df = 3; 51) 5.785*** (df = 4; 50)
## =============================================================================================
## Note:                                                       *p<0.1; **p<0.05; ***p<0.01
```

```r
apa.reg.table(m1, filename = "regressiontable_gpa1.doc")
```

```
##
## MBESS package needs to be installed to calculate R2 confidence intervals.
```

```
##
##
## Regression results using finalgrade as the criterion
##
##
##    Predictor      b      b_95%_CI beta   beta_95%_CI sr2  sr2_95%_CI     r
##  (Intercept) 34.50* [6.59, 62.42]
##          ses   2.69 [-0.83, 6.20] 0.20 [-0.06, 0.46] .04 [-.05, .13]  .27*
##         hgpa  0.42*  [0.06, 0.78] 0.31  [0.04, 0.57] .09 [-.05, .23] .35**
##
##
##
##           Fit
##
##
##
##     R2 = .162*
##  95% CI[NA,NA]
##
##
## Note. A significant b-weight indicates the beta-weight and semi-partial correlation are also significant.
## b represents unstandardized regression weights. beta indicates the standardized regression weights.
## sr2 represents the semi-partial correlation squared. r represents the zero-order correlation.
## Square brackets are used to enclose the lower and upper limits of a confidence interval.
## * indicates p < .05. ** indicates p < .01.
##
```

```r
apa.reg.table(m2,m3, filename = "regressiontable_gpa.doc")
```

```
##
## MBESS package needs to be installed to calculate R2 confidence intervals.
##
## MBESS package needs to be installed to calculate R2 confidence intervals.
```

```
##
##
## Regression results using finalgrade as the criterion
##
##
##                    Predictor      b        b_95%_CI sr2  sr2_95%_CI
##                  (Intercept)  26.79  [-0.12, 53.71]
##                          ses   2.49   [-0.82, 5.80] .03 [-.05, .11]
##                         hgpa 0.47**    [0.13, 0.81] .11 [-.03, .25]
##     interventionIntervention 7.52**   [2.03, 13.02] .11 [-.03, .25]
##
```

```
##
##
##                   (Intercept) -11.04 [-59.97, 37.89]
##                           ses   2.20   [-1.06, 5.45] .03 [-.04, .09]
##                          hgpa 0.95**    [0.33, 1.56] .13 [-.02, .28]
##      interventionIntervention 60.28*  [2.51, 118.04] .06 [-.05, .17]
##  hgpa:interventionIntervention  -0.66   [-1.38, 0.06] .05 [-.05, .14]
##
##
##
##           Fit        Difference
##
##
##
##
##    R2 = .270**
##  95% CI[NA,NA]
##
##
##
##
##
##
##    R2 = .316**   Delta R2 = .046
##  95% CI[NA,NA] 95% CI[-.05, .14]
##
##
## Note. A significant b-weight indicates the semi-partial correlation is also significant.
## b represents unstandardized regression weights.
## sr2 represents the semi-partial correlation squared.
## Square brackets are used to enclose the lower and upper limits of a confidence interval.
## * indicates p < .05. ** indicates p < .01.
##

#### Correlation Tables ----

#correlation table at pre
apa.cor.table (dat[c("age","gender","ses","hgpa","tm_m","spuss_m","sacq_m", "pss_m","cesd_m")],
               filename = "cortable_pre.doc")

##
##
## Means, standard deviations, and correlations with confidence intervals
##
##
##   Variable   M     SD   1           2           3           4
##   1. age     19.61 1.72
##
##   2. ses     2.03  0.85 -.12
##                         [-.37, .14]
##
##   3. hgpa    79.73 8.17 -.03        .25
##                         [-.28, .23] [-.01, .48]
##
##   4. tm_m    2.53  0.59 .14         .04         .44**
##                         [-.12, .39] [-.22, .30] [.20, .62]
##
##   5. spuss_m 6.10  0.96 .14         -.09        -.09        .28*
##                         [-.12, .38] [-.34, .17] [-.34, .17] [.03, .50]
##
##   6. sacq_m  5.74  1.11 .37**       .10         .24         .55**
##                         [.12, .57]  [-.16, .34] [-.01, .47] [.35, .71]
##
##   7. pss_m   1.71  0.55 -.20        .20         .21         -.18
##                         [-.44, .06] [-.06, .43] [-.05, .44] [-.42, .08]
##
##   8. cesd_m  0.85  0.47 -.12        .03         .12         -.01
##                         [-.36, .15] [-.23, .29] [-.14, .37] [-.27, .24]
##
##   5            6            7
##
##
##
```

```
##
##
##
##
##   .43**
##   [.20, .62]
##
##   -.43**       -.40**
##   [-.62, -.20] [-.59, -.16]
##
##   -.29*        -.34**       .66**
##   [-.51, -.04] [-.55, -.09] [.49, .79]
##
##
## Note. M and SD are used to represent mean and standard deviation, respectively.
## Values in square brackets indicate the 95% confidence interval.
## The confidence interval is a plausible range of population correlations
## that could have caused the sample correlation (Cumming, 2014).
## * indicates p < .05. ** indicates p < .01.
##
```

```
#correlation table at post - control
apa.cor.table( subset(dat[c("hgpa","tm_m","spuss_m","sacq_m", "pss_m","cesd_m",
                            "tm_postm","spuss_postm","sacq_postm", "pss_postm","cesd_postm")],
             dat$intervention == "Control" & dat$post == 1),
              filename = "cortable_postcontrol.doc")
```

```
##
##
## Means, standard deviations, and correlations with confidence intervals
##
##
##   Variable       M     SD   1            2            3
##   1. hgpa        80.42 6.78
##
##   2. tm_m        2.48  0.54 .35
##                             [-.06, .66]
##
##   3. spuss_m     6.02  0.95 .16          .44*
##                             [-.26, .53] [.05, .72]
##
##   4. sacq_m      5.68  1.11 .37          .68**        .42*
##                             [-.04, .67] [.39, .85]   [.02, .71]
##
##   5. pss_m       1.77  0.53 .30          -.19         -.33
##                             [-.12, .63] [-.55, .23]  [-.65, .08]
##
##   6. cesd_m      0.79  0.43 .20          -.17         -.23
##                             [-.22, .56] [-.54, .25]  [-.58, .19]
##
##   7. tm_postm    2.17  0.65 .15          .48*         -.27
##                             [-.27, .52] [.09, .74]   [-.61, .15]
##
##   8. spuss_postm 6.31  1.02 .18          .50*         .44*
##                             [-.24, .54] [.12, .75]   [.04, .71]
##
##   9. sacq_postm  5.03  1.06 .31          .58**        .11
##                             [-.11, .63] [.23, .80]   [-.31, .49]
##
##   10. pss_postm  2.33  0.63 .06          -.42*        -.04
##                             [-.35, .46] [-.71, -.03] [-.43, .37]
##
##   11. cesd_postm 1.23  0.53 -.09         -.32         -.16
##                             [-.48, .33] [-.64, .10]  [-.53, .26]
##
##   4            5            6           7           8
##
##
##
##
##
##   -.40
##   [-.69, .01]
```

```
##
##   -.33         .70**
##   [-.65, .08]  [.41, .86]
##
##   .25          .12          .14
##   [-.17, .60]  [-.30, .50]  [-.28, .52]
##
##   .71**        -.57**       -.40        -.05
##   [.42, .86]   [-.79, -.22] [-.69, .00] [-.44, .36]
##
##   .69**        -.18         -.06        .43*        .32
##   [.39, .85]   [-.55, .24]  [-.45, .35] [.03, .71]  [-.09, .64]
##
##   -.66**       .50*         .48*        -.36        -.51*
##   [-.84, -.36] [.12, .75]   [.10, .74]  [-.67, .05] [-.76, -.14]
##
##   -.50*        .36          .51*        -.23        -.44*
##   [-.75, -.13] [-.05, .67]  [.13, .76]  [-.58, .19] [-.72, -.05]
##
##   9            10
##
##
##
##
##   -.68**
##   [-.85, -.38]
##
##   -.50*        .68**
##   [-.75, -.13] [.38, .85]
##
##
## Note. M and SD are used to represent mean and standard deviation, respectively.
## Values in square brackets indicate the 95% confidence interval.
## The confidence interval is a plausible range of population correlations
## that could have caused the sample correlation (Cumming, 2014).
## * indicates p < .05. ** indicates p < .01.
##
```

```r
#correlation table at post - intervention
apa.cor.table( subset(dat[c("hgpa","tm_m","spuss_m","sacq_m", "pss_m","cesd_m",
                            "tm_postm","spuss_postm","sacq_postm", "pss_postm","cesd_postm")],
                      dat$intervention == "Intervention" & dat$post == 1),
               filename = "cortable_postintervention.doc")
```

```
##
##
## Means, standard deviations, and correlations with confidence intervals
##
##
##   Variable       M     SD   1           2           3
##   1. hgpa        78.81 9.38
##
##   2. tm_m        2.60  0.62 .49**
##                             [.17, .72]
##
##   3. spuss_m     6.23  0.99 -.17        .18
##                             [-.50, .19] [-.18, .51]
##
##   4. sacq_m      5.80  1.12 .15         .42*        .51**
##                             [-.22, .48] [.07, .67]  [.19, .73]
##
##   5. pss_m       1.64  0.54 .24         -.04        -.56**
##                             [-.13, .55] [-.39, .32] [-.77, -.26]
##
##   6. cesd_m      0.85  0.49 .11         .16         -.38*
##                             [-.25, .45] [-.20, .49] [-.64, -.02]
##
##   7. tm_postm    2.75  0.54 .53**       .43*        -.15
##                             [.22, .75]  [.09, .68]  [-.48, .22]
##
##   8. spuss_postm 6.39  1.05 -.01        .04         .61**
##                             [-.37, .34] [-.31, .39] [.32, .79]
##
```

```
##   9. sacq_postm  6.08  1.01 .23         .33         .48**
##                             [-.13, .54] [-.03, .61] [.16, .72]
##
##   10. pss_postm  1.64  0.72 -.15        -.15        -.38*
##                             [-.48, .22] [-.48, .21] [-.65, -.03]
##
##   11. cesd_postm 1.12  0.50 -.04        .05         -.20
##                             [-.39, .32] [-.31, .40] [-.52, .16]
##
##   4           5            6            7            8
##
##
##
##
##
##
##   -.33
##   [-.61, .03]
##
##   -.32        .64**
##   [-.61, .03] [.37, .81]
##
##   .25         .26          -.09
##   [-.12, .55] [-.11, .56]  [-.43, .27]
##
##   .33         -.39*        -.24         -.08
##   [-.03, .61] [-.65, -.04] [-.55, .13]  [-.42, .28]
##
##   .62**       -.29         -.42*        .47**        .44*
##   [.34, .80]  [-.58, .07]  [-.67, -.07] [.14, .71]   [.10, .69]
##
##   -.33        .18          .46**        -.48**       -.36*
##   [-.61, .03] [-.18, .50]  [.12, .70]   [-.71, -.15] [-.63, -.01]
##
##   .03         .40*         .68**        -.19         .00
##   [-.33, .38] [.05, .66]   [.43, .83]   [-.51, .17]  [-.35, .36]
##
##   9            10
##
##   -.79**
##   [-.89, -.60]
##
##   -.37*        .53**
##   [-.64, -.02] [.22, .75]
##
##
## Note. M and SD are used to represent mean and standard deviation, respectively.
## Values in square brackets indicate the 95% confidence interval.
## The confidence interval is a plausible range of population correlations
## that could have caused the sample correlation (Cumming, 2014).
## * indicates p < .05. ** indicates p < .01.
##
```

Appendix D: Study One Protocols

T2U - CANADA

Research Code: ______

Transition to University Research Project

In order that we are able to contact you once you have started university we need you to provide us with some information. If you know where you will be living once you begin university, please provide your new information below. Additionally, please provide us with the name, phone number and address of a parent and one other person who probably will know where to contact you once you have started university.

The information on this page will be stored in a separate site from the remainder of your responses. We will only be using this information to locate you at university and to match this information up with that gathered in later questionnaires.

Your Name: ________________________________ Your University Address: (please print) ____ Your University ID # _______________________ Phone number: ____________________________ e-mail: ____________________________________	Parent's: Name: ____________________________________ Address: _______________________________ _________________________________ _________________________________ Phone number: ___________________________
Someone Else: (this should be someone with whom you'll be in contact for several years, and who is unlikely to move - maybe a grandparent or another relative?) Name: _____________________________________ Address: _________________________________ _________________________________ Phone Number: _____________________________	Thank you for your interest in our research project. We hope you will benefit personally from your participation. You will also be contributing to an important program of psychological research.

What university will you be attending in September:

___ Memorial University of Newfoundland
___ University of Guelph
___ University of Toronto - Erindale
___ University of Toronto - St. George
___ Wilfrid Laurier University
___ York University

T2U - CANADA
TRANSITION TO UNIVERSITY RESEARCH

Principal Investigators: (listed alphabetically)
Gerald Adams (University of Guelph)
Shelly Birnie-Lefcovich (Memorial University of Newfoundland)
S. Mark Pancer (Wilfrid Laurier University)
Janet Polivy (University of Toronto)
Michael Pratt (Wilfrid Laurier University)
Maxine Gallander Wintre (York University)

______

- Are you… □ male □ female
- Graduating high school average: ___%
- Financially, do you consider your family to be:
  □ Below average income
  □ Average income
  □ Above average income
  □ Well above average income

Time Management

Below you will find a number of statements about approaches people take with regard to managing their time at university. Please indicate how often you do each of the following using the scale below:

0	1	2	3	4
never	almost never	sometimes	fairly often	very often

1. _____ I set goals for myself to keep up with my due dates.
2. _____ I study someplace where it is quiet and distractions are limited.

R 3. _____ I avoid my assignments until they are almost due.

4. _____ I make keeping up with course work my first priority.
5. _____ I try to manage my "school-work time" as well as my "play time" to make the best out of both.
6. _____ I follow a regular study program.

R 7. _____ I don't worry much about school work; I'll get around to it when I can.

8. _____ I get down to serious studying early in the year so that I do not fall behind.
9. _____ I try to estimate how much time I will need to complete an assignment or essay and then give myself plenty of time to complete it.

R 10. _____ I put off studying for courses I don't like or that are difficult.

11. _____ I plan when I will study and when I will go out with my friends.

R 12. _____ If I have an assignment due, I leave it until the last day and work on it until I finish it.

13. _____ I like to plan when and for how long I will work on an assignment.
14. _____ I schedule my due dates on a calendar to guide my time for studying/doing assignments.

R 15. _____ I need a certain amount of stress/pressure to start working on an assignment/study for a test.

16. _____ It's important for me to stick to my planned schedule of studying.
17. _____ If I have an assignment coming up, I start it way before it is due.

R 18. _____ I will go out with my friends anytime they ask, no matter how much work I have to do.

19. _____ I attend all my lectures and tutorials.

R 20. _____ When it comes to school work, I don't worry about planning when I will do it, I just do it when I can.

21. _____ I outline a study plan and commit to it.
22. _____ I start studying for tests early so that I have lots of time to review the material.

Students' Perception of University Support and Structure

Please use the following scale to indicate your agreement with each statement, as it applies to this university.

-4	-3	-2	-1	0	+1	+2	+3	+4
very strongly disagree	strongly disagree	moderately disagree	slightly disagree	neither agree nor disagree	slightly agree	moderately agree	strongly agree	very strongly agree

1. _____ Students are informed during student orientation about help available to them if they are having any emotional or adjustment problems.
2. _____ The degree and program requirements in the university calendar are very clear.
3. _____ It's easy to make friends.
4. _____ Professors in classes make it clear what students are expected to do in order to get a good grade on assignments, papers and tests.
5. _____ If a student needed help for an emotional problem, it would be easy to find a service on campus to help them.
6. _____ Professors aren't really clear about what they expect of students.
7. _____ There are lots of confusing rules that make registration and course selection difficult.
8. _____ The professors don't really care about their students.
9. _____ There aren't many places for students to get together and talk.
10. _____ If students are having difficulty with academic course work, they can easily talk to professors or their teaching assistants.
11. _____ Professors at this school don't really try to make you think.
12. _____ Professors get tests and assignments back to students in good time.
13. _____ It is hard for students to get advice in selecting courses or deciding on a program of study.
14. _____ Professors and teaching assistants in classes are helpful and encouraging.
15. _____ Academic policies on cheating and copying are made clear to students.
16. _____ Professors and teaching assistants don't give very much feedback on tests, exams or papers.
17. _____ There's very little opportunity for students to have direct one-to-one contact with a professor.
18. _____ Professors emphasize reasoned questions and critical appraisal of what they present in class.
19. _____ Faculty and teaching assistants post office hours and are available when they say they will be.
20. _____ School officials and advisors are approachable and open-minded when you have a question or problem.

CES-D: Thoughts and Feelings

0	1	2	3
rarely or none of the time (less than 1 day)	some or a little of the time (1-2 days)	occasionally or a moderate amount of time (3-4 days)	most or all of the time (5-7 days)

During the <u>past week</u>:

1. I was bothered by things that usually don't bother me.
2. I did not feel like eating; my appetite was poor.
3. I felt that I could not shake off the blues even with help from my family or friends.
4. I felt that I was just as good as other people.
5. I had trouble keeping my mind on what I was doing.
6. I felt depressed.
7. I felt that everything I did was an effort.
8. I felt hopeful about the future.
9. I thought my life had been a failure.
10. I felt fearful.
11. My sleep was restless.
12. I was happy.
13. I talked less than usual.
14. I felt lonely.
15. People were unfriendly.
16. I enjoyed life.
17. I had crying spells.
18. I felt sad.
19. I felt that people dislike me.
20. I could not get "going".

Perceived Stress Scale

0	1	2	3	4
never	almost never	sometimes	fairly often	very often

In the past month, how often have you ….

1. ___ been upset because of something that happened unexpectedly?
2. ___ felt that you were unable to control the important things in your life?
3. ___ felt nervous and “stressed”
4. ___ dealt successfully with irritating life’s hassles?
5. ___ felt that you were effectively coping with important changes that were occurring in your life?
6. ___ felt confident about your ability to handle your personal problems?
7. ___ felt that things were going your way?
8. ___ Found that you could not cope with all the things that you had to do?
9. ___ been able to control irritations in your life?
10. ___ felt that you were on top of things?

11. ___ been angered because of things that happened that were outside of your control?
12. ___ found yourself thinking about things that you have to accomplish?
13. ___ been able to control the way you spend your time?
14. ___ Felt difficulties were piling up so high that you could not overcome them?

Student Adaptation to College Questionnaire

The 67 items included in this survey are statements that describe university experiences. Read each one and decide how well it applies to you at the present time (within the last few days). For each item, record the appropriate number in the space next to that item.

1	2	3	4	5	6	7	8	9
Doesn't apply to me at all								Applies very closely to me

1. ______ I feel that I fit in well as part of the university environment.
2. ______ I have been feeling tense or nervous lately.
3. ______ I have been keeping up to date on my academic work.
4. ______ I am meeting as many people, and making as many friends as I would like at university.
5. ______ I know why I'm in university and what I want out of it.
6. ______ I am finding academic work at university difficult.
7. ______ Lately I have been feeling blue and moody a lot.
8. ______ I am very involved with social activities in university.
9. ______ I am adjusting well to university.
10. ______ I have not been functioning well during examinations.
11. ______ I have felt tired much of the time lately.
12. ______ Being on my own, taking responsibility for myself, has not been easy.
13. ______ I am satisfied with the level at which I am performing academically.
14. ______ I have had informal, personal contacts with university professors.
15. ______ I am pleased now about my decision to go to university.
16. ______ I am pleased now about my decision to attend this university in particular.
17. ______ I'm not working as hard as I should at my course work.
18. ______ I have several close social ties at university.
19. ______ My academic goals and purposes are well defined.
20. ______ I haven't been able to control my emotions very well lately.
21. ______ I'm not really smart enough for the academic work I am expected to be doing now.
22. ______ Lonesomeness for home is a source of difficulty for me now.
23. ______ Getting a university degree is very important to me.
24. ______ My appetite has been good lately.
25. ______ I haven't been very efficient in the use of study time lately.
26. ______ I enjoy living in a university residence. (Or any university housing.)
27. ______ I enjoy writing papers for courses.
28. ______ I have been having a lot of headaches lately.
29. ______ I really haven't had much motivation for studying lately.
30. ______ I am satisfied with the extracurricular activities available at university.
31. ______ I've given a lot of thought lately to whether I should ask for help from the

Psychological/Counselling Services Centre or from a counsellor outside of university.

32. _______ Lately I have been having doubts regarding the value of a university education.
33. _______ I am getting along very well with my roommate(s) at university.
34. _______ I wish I were at another university.
35. _______ I've put on (or lost) too much weight recently.
36. _______ I am satisfied with the number and variety of courses available at university.
37. _______ I feel that I have enough social skills to get along well in the university setting.
38. _______ I have been getting angry too easily lately.
39. _______ Recently I have had trouble concentrating when I try to study.
40. _______ I haven't been sleeping very well.
41. _______ I'm not doing well enough academically for the amount of work I put in.
42. _______ I am having difficulty feeling at ease with other people at university.
43. _______ I am satisfied with the quality or calibre of courses available at university.
44. _______ I am attending classes regularly.
45. _______ Sometimes my thinking gets muddled up too easily.
46. _______ I am satisfied with the extent to which I am participating in social activities at university.
47. _______ I expect to stay at this university for a bachelor's degree.
48. _______ I haven't been mixing too well with the opposite sex lately.
49. _______ I worry a lot about my university expenses.
50. _______ I am enjoying my academic work at university.
51. _______ I have been feeling lonely a lot at university lately.
52. _______ I am having a lot of trouble getting started on homework assignments.
53. _______ I feel I have good control over my life situation at university.
54. _______ I am satisfied with my program of courses for this term.
55. _______ I have been feeling in good health lately.
56. _______ I feel I am very different from other students at university in ways that I don't like.
57. _______ On balance, I would rather be home than here.
58. _______ Most of the things I am interested in are not related to any of my course work at university.
59. _______ Lately I have been giving a lot of thought to transferring to another university.
60. _______ Lately I have been giving a lot of thought to dropping out of university altogether and for good.
61. _______ I find myself giving considerable thought to taking time off from university and finishing later.
62. _______ I am very satisfied with the professors I have now in my courses.
63. _______ I have some good friends or acquaintances at university with whom I can talk about any problems I may have.
64. _______ I am experiencing a lot of difficulty coping with the stresses imposed on me in university.
65. _______ I am quite satisfied with my social life at university.
66. _______ I am quite satisfied with my academic situation at university.
67. _______ I feel confident that I will be able to deal in a satisfactory manner with future challenges here at university.

Appendix E: Study Two Protocols.

Communication with Students and Sign up Form

Email Subject: URPP Study Opportunity

Dear students,
This email is to invite you to **earn 2 URPP credits** by attending a short workshop.
To take advantage of this opportunity please read the following carefully:
The workshops are being held on 4 different days at 5:30 pm (Monday January 30 to Thursday February 2), and you should **only attend one of them, and save your spot by signing up online using the link below** (workshop space is limited to 15 students each day). The workshops will take about an hour, during which we will discuss skills and issues that are relevant to learning, doing well in University, and the common challenges students face. **And there will be coffee, tea and cookies! :)**
So there will be 4 opportunities to attend the workshop:

Date	Time	Location
Monday January 30	5:30 to 6:40 pm	Behavioural Sciences Building
Tuesday January 31	5:30 to 6:40 pm	Behavioural Sciences Building
Wednesday February 1	5:30 to 6:40 pm	Behavioural Sciences Building
Thursday February 2	5:30 to 6:40 pm	Behavioural Sciences Building

In order to attend the workshop and earn 2 URPP credits, you need to sign up in advance by filling out this short survey.
The link to the survey is below, **please read and answer each question carefully:** SURVEY LINK
Students who participate in Academic Skills Workshop and Discussion group will have the opportunity to earn an additional URPP credit (on top of 2 you receive for participation) at the end of the term by filling out a short survey. You will be contacted about it during March 2017. So in total, you can get 3 URPP credits out of the 6 you need, just make sure to get the other 3 credits from different studies by the end of March and you are all set!
****In order to complete this survey and attend the workshop you need to have an URPP identification number,** if you haven't already signed up for the URPP you can sign up here: URPP LINK

Thank you,

URPP Study Description:

Academic Skills and University Challenges Workshop Discussion Group

Dear students, You are invited to participate in a short survey followed by a workshop discussing various topics relevant to adjusting to the demands of University education. The Survey will take about 20 minutes to complete, and the workshop will take less than an hour. You are give TWO URPP participation credits for participating in both parts.

There will be another opportunity at the end of the term to fill out a short survey for an additional URPP credit - this will be open only to students who have participated in this workshop.

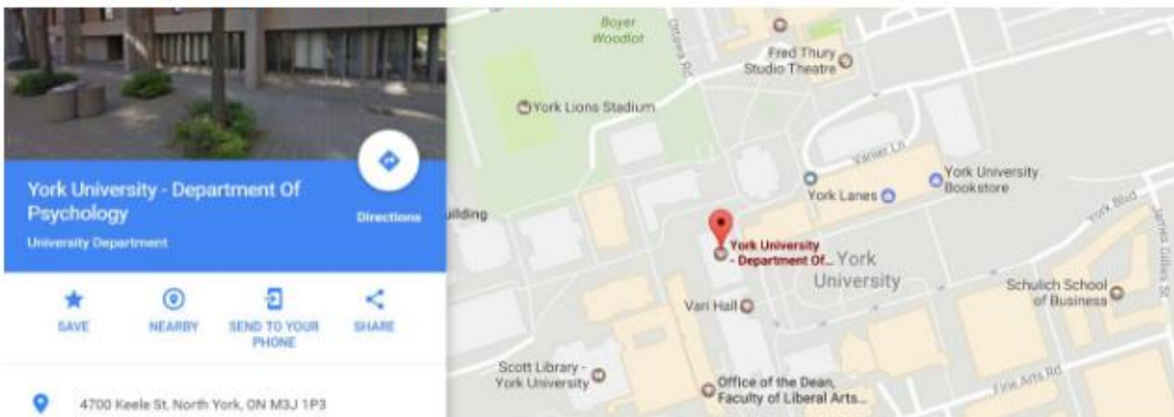
There are four workshops being held, you **should only attend one** of them. Please make sure that you are signing up for the one that best fits your schedule - the workshops are held at 5:25 pm on Monday January 30, Tuesday Jan 31, Wednesday February 1, and Thursday February 2. The location of the workshops is Behavioural Sciences Building Room 061

Academic Skills and University Challenges

Workshop Signup

You can signup for a workshop below, please note you should only attend one workshop.
All workshops will be held at the Behavioural Sciences Building room 061.
The workshops will **start at 5:25 pm** and **finish before 6:45 pm**, giving you plenty of time to make your evening classes.
There will be coffee, tea and cookies to keep help you stay awake :)

Location of the Workshop (Behavioural Sciences Building)



1. Below are the 4 options you have for attending a workshop. Workshops are held on Monday, Tuesday, Wednesday and Thursday during the week of January 30. You will receive an email confirmation few days before the workshop reminding you about the time and location.

- MONDAY JAN 30 @ 5:25 PM
- TUESDAY JAN 31 @ 5:25 PM
- WEDNESDAY FEB 1 @ 5:25 PM
- THURSDAY FEB 2 @ 5:25 PM

Change in Knowledge

The ideas below are studied by psychologists and in the field of psychology. Have you studied them before, if so, how well do you know them? (if you don't know, that's ok, these topics may not be covered in the first year course you are taking)

	Don't know it	Know it slightly	Know a few things about it	Know some things about it	Know a fair bit about it
Ego Depletion	○	○	○	○	○
Precommitment Strategies	○	○	○	○	○
Decision Fatigue	○	○	○	○	○
Pomodoro Technique	○	○	○	○	○
Impact of Multitasking on Attention and Learning	○	○	○	○	○

Workshop Consent

Thank you for your involvement in our study and participating in the Academic Skills and University Challenges Workshop and Discussion Group. This workshop, which will take about 50 minutes to complete, will involve a discussion on various tips and tools related to your experience at university. At the end of the workshop, we will present you with a brief questionnaire where you can tell us how useful you found this experience.

Your participation in our research is completely voluntary; you may leave the workshop at any time or omit any questions, although it is most helpful to us if you complete the entire workshop and answer the feedback survey. Your responses will be kept completely confidential, and confidentiality will be provided to the fullest extent possibly by law. Your name will not be used or associated with any of the data collected. If we do use direct quotations in any related publications all identifying information will be removed. We do not foresee any risks as a result of your participation in this component of the study. Data will be stored in a secure database on a password protected computer for the duration of the study after which it will be destroyed.

You will receive one URPP credit for participating in this workshop. Your decision to stop participating, or to refuse to answer particular questions, will not affect the credit that you will receive, your relationship with the researchers, York University, or any other group associated with this project. In the event you wish to withdraw from the study, please inform the researchers and all previously collected and associated data will be immediately destroyed wherever possible. You will receive one academic credit for participating in this study. Your decision to stop participating, or to refuse to answer particular questions, will not affect the credit that you will receive, your relationship with the researchers, York University, or any other group associated with this project.

This research has received ethics review and approval by the Human Participants Review Sub-Committee, York University's Ethics Review Board and conforms to the standards of the Canadian Tri-Council Research Ethics guidelines. If you have any questions about this process, or about your rights as a participant in the study, please contact the Sr. Manager & Policy Advisor for the Office of Research Ethics, 5th Floor, Kaneff Tower, York University (telephone ### or e-mail EMAIL). If you have any questions about the questionnaire or the research project, please contact Saeid Chavoshi (EMAIL).

Once again, thank you for your co-operation with our research project.

I've Read and understood this consent – sign : ________________________

Name:

URPP Number:

Intervention Workshop Student Handout

Multi-Tasking – main ideas:

Multi-Tasking – action plans:

>

>

>

Notes:

Ego Depletion – main ideas:

Ego Depletion – action plans:

>

>

>

Notes:

Decision Fatigue – main ideas:

Decision Fatigue – action plans:

>

>

>

Notes:

	Monday	Tuesday	Wednesday	Thursday	Friday
8-9					
9-10					
10-11					
11-12					
12-1					
1-2					
2-3					
3-4					
4-5					
5-6					
6-7					
7-8					
8-9					

Control Group Workshop Facilitation Questions

1. What are some of the challenges you've faced since you started university?
2. What are some lessons you've learned that have helped you adapt to university life?
3. What are some early actions or steps that you took which were helpful?
4. What is one thing you would do differently if you could go back to September?
5. If you could send your September self a text message to help him/her do better in University what would it say?
6. What are the best sources of support, whether people, websites, or other resources, that you've discovered?
7. Where are the best places to study on campus? Eat? Get coffee? Exercise? Hangout?
8. What is the best academic experience you've had so far?
9. What have you enjoyed learning about the most in your courses so far?
10. What has been your most challenging academic experience so far and how did you work through it?

Appendix F: Intervention Workshop Slides

- Multitasking
- Ego Depletion
- Decision Fatigue

1

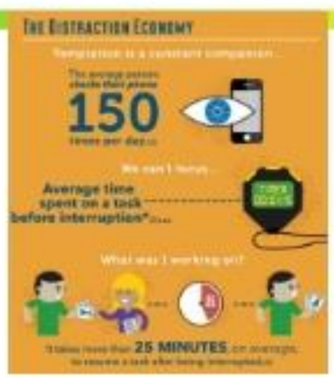
Multitasking

Multitasking DOES NOT WORK!

2

3

4



5

6

7

8

9

10

1.Multitasking, by using a laptop for non-class related activities while also paying attention to the lecture and taking notes, has a detrimental effect on learning of the student with the laptop. That is an unsurprising result that has been seen before, but it is confirmed here with a particularly careful study.

2.Most important result—there is a substantial negative impact on the learning of the students that are not using laptops and are paying attention to the lecture but are able to see a laptop that is being used for non-class activities.

11

- In an experiment involving 62 undergraduate students taking a principles of accounting course, half of the cohort was allowed to text during a lecture and **half had their phones turned off**. After the lecture both groups took the same quiz and the students who did not text scored significantly higher on the quiz.Ellis, Y., Daniels, W. and Jauregui, A. (2010). The effect of multitasking on the grade performance of business students. Research in Higher Education Journal, 8http://www.aabri.com/manuscripts/10498.pdf

12

- A cross-disciplinary cohort of 774 students responded to a survey which documented that the majority of them engaged in classroom multitasking. **Their multitasking was significantly related to lower GPA and to an increase in risk behaviors including use of alcohol, tobacco and other drugs**. Barak, L. (2012). Multitasking in the university classroom. *International Journal for the Scholarship of Teaching and Learning, 6* (2)http://academics.georgiasouthern.edu/ijsotl/v6n2.html.

13

Multitasking
- Not just ineffective, but can have lasting negative effects.

14

Always switched on: what years of multitasking does to our brains

We've been doing productivity wrong.

15

Switching between browser tabs or different jobs might give you a false sense of productivity, but you're in fact working less efficiently across every task: we leave behind what's known as 'attention residue' when jumping from job to job.

The research backs up what Newport says. Multitasking - which is actually quickly switching between tasks rather than doing any of them simultaneously - can reduce your productivity by up to 40 percent. It also impairs the ability of our brains to learn new skills. There's even some evidence that multitasking too often causes permanent damage to the brain.

16

Brain Damage From Multitasking

It was long believed that cognitive impairment from multitasking was temporary, but new research suggests otherwise. Researchers at the University of Sussex in the UK compared the amount of time people spend on multiple devices (such as texting while watching TV) to MRI scans of their brains. They found that high multitaskers had less brain density in the anterior cingulate cortex, a region responsible for empathy as well as cognitive and emotional control.

17

Why is it so hard to stop?

18

Social Media Triggers a Dopamine High

Social media affects the brain in the same way that a hug does. Here's how it works, and what marketers can do about it.

19

Why We're All Addicted to Texts, Twitter and Google

Dopamine makes you addicted to seeking information in an endless loop.

The culprit is dopamine —

20

Multitasking

- Key takeaways?

21

Breaking Tasks into Meaningful Chunks

http://faculty.bucks.edu/specpop/chunks.htm

Then take breaks!

22

Productivity 101: A Primer to The Pomodoro Technique

http://lifehacker.com/productivity-101-a-primer-to-the-pomodoro-technique-1598992730

23

http://pomodoneapp.com

24

The Best Pomodoro Timer Apps

App	Best for	Price	Platform
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]

25

Multitasking
- What can you do?

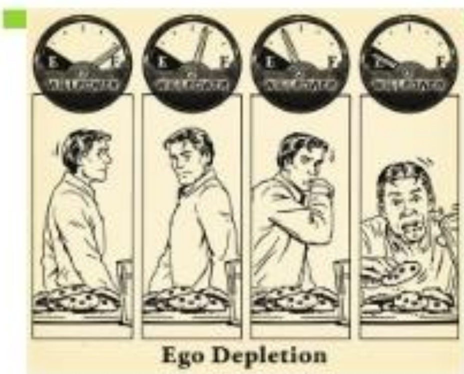
Come up with a few actionable ideas

26

Ego Depletion

Willpower is a finite resource

27



28

29

Ego Depletion

- being tired/ lack of sleep makes self control harder

-sleep and rest (even a small break – or a nap!) can be restorative

-beware of hunger! ->snacks

30

Ego Depletion

- Key takeaways?

31

Web-blockers are tools to structure your digital environment, so you don't have to constantly fight the impulse to on Facebook/Youtube/ETC

32

Web-blockers can block your access to the internet for an amount of time you choose – or block your access to specific websites that you pick

33

Managing Digital Temptations…

- www.freedom.to

34

Managing Digital Temptations…

35

36

37

Knowing where you are helps – track your own behaviour (feedback)

38

39

Ego Depletion
- What can you do?

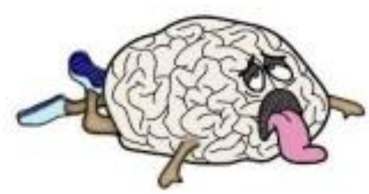
Come up with a few actionable ideas

40

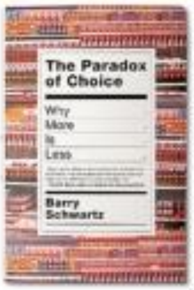
Decision Fatigue

41

After shopping…



42



*"...The fact that some choice is good doesn't necessarily mean that more choice is better...there is a cost to having an overload of choice. As a culture we are enamoured of freedom, self-determination, and variety, and we are reluctant to give up any options. But clinging tenaciously to all the choices available to us contributes to **bad decisions, to anxiety, stress, and dissatisfaction**...*

43

lifehacker

How to Overcome Decision Fatigue

- **Make vital decisions early in the day...**
- **Also try to do the most important work in the morning.** If I have an important life decision to make, I try to do it earlier in the day.

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Decision Fatigue
- what are some main takeaways?

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Decision Fatigue
- What can you do?

Come up with a few actionable ideas

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Avoiding Decision Fatigue through habits

- Dedicating **pre-planed** Time and Space to studying
  - Especially if one or two hour blocks between classes
  - Be concrete
- **Postpone unnecessary activities until the work is done (eg checking email)**

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